Capital Market Integration for Innovation-Led Growth*

Isabel Figueiras†

Click here for latest version

November 17, 2026

Abstract

This paper studies how capital market integration shapes innovation-led growth and the spatial distribution of innovation. I develop a multi-country endogenous growth model in which households save through a risk-free asset or venture capital (VC), subject to participation costs in VC. Locations are heterogeneous in innovation opportunities and venture capitalists can invest in domestic and foreign entrepreneurs, but face cross-border information and regulatory barriers that make foreign investments costly. To quantify this framework, I use micro-level data on venture capital deals to construct bilateral investment matrices across US states and EU countries and combine them with patent data to study differences in innovation patterns. I document that i) European households invest less in risky assets, ii) European investors are more home-biased, and iii) US investors provide a share of the funding of European startups comparable to that of investors in other European countries. I calibrate the model to match these investment patterns and study the effects of deeper financial integration on productivity growth in the EU. A combined policy that mobilises European savings while integrating capital markets has the largest effects on productivity and growth. A policy that only reduces cross-border frictions has limited effects on growth because savings remain trapped in risk-free assets. Lower participation costs raise the amount EU households invest in VC, but part of the new funding goes to the US and much of the rest replaces foreign investors in EU startups.

JEL Codes: F36, F43, G24, O31, O40.

Keywords: Capital market integration, Innovation, Endogenous growth, Venture capital.

*I am grateful to my advisor Luca Fornaro for continuous guidance and support. I thank Vladimir Asriyan, Fernando Broner, Davide Busnelli, Andrea Caggese, Jeanne Commault, Marta Cota, José Alberto Ferreira, Madalena Gaspar, Priit Jeenas, Benjamin Klaus, Thomas Lazarowicz, Luca Looser, Clément Malgouyres, Alberto Martin, Dávid Krisztián Nagy, Clément Nedoncelle, Hugo Reichardt, Maria Agustina Sampaolesi, Edouard Schaal, André Terreri Rodrigues, Jaume Ventura, Carolina Villegas-Sanchez, Ying Wang, and Robert Zymek, as well as many seminar and conference participants for helpful comments and discussions. All errors are my own.

†Universitat Pompeu Fabra and Barcelona School of Economics. Email: isabel.figueiras@upf.edu.

1 Introduction

Growth in the European Union has been subdued over the past two decades, and the productivity gap relative to the United States has widened since the 1990s. A central policy hypothesis is that Europe's fragmented equity markets limit the ability of savings to finance high-growth innovative firms, a concern often discussed in the context of the Capital Markets Union (Lagarde, 2024). European startups frequently report financing constraints and struggle to scale across national markets, despite high household saving rates (EIB, 2024b). While integration has increased in bond markets, equity portfolios still display a strong degree of home bias (Beck et al., 2024). If capital cannot move easily across regions, savings may remain trapped in lower-return domestic projects even when more productive innovation opportunities exist elsewhere.

Venture capital (VC) is a source of equity finance that is particularly important for financing young innovative firms. A large empirical literature shows that VC-backed firms innovate more and generate higher quality patents than similar firms financed through other channels (Lerner and Nanda, 2020). However, the European VC sector remains smaller and less integrated than its US counterpart (Asdrubali, 2023; Arnold, Claveres and Frie, 2024). Factors such as limited knowledge of foreign markets, distance to target firms, and the regulatory and bureaucratic burdens are often cited as key barriers to cross-border investments within the EU (EIB, 2024a). Whether these frictions are large enough to meaningfully distort the allocation of risk capital, and reduce growth and innovation, remains an open question.

This paper studies how lowering the cost of cross-border venture capital investment shapes innovation, growth, and the spatial allocation of entrepreneurial activity. Using data on venture capital deals, I construct bilateral matrices of VC investment across US states and across EU countries, and document three patterns. First, cross-border VC flows are much more developed across US states than across EU countries. Second, US investors account for a share of funding into European startups that is comparable to that coming from cross-border investment within the EU itself. Third, home bias is larger and VC activity is more spatially dispersed in Europe, while the US exhibits stronger agglomeration of funding in a small number of high-return hubs.

Different factors can explain the lower levels of VC, cross-border investment and agglomeration. The reason behind the low level of VC investment might come from the demand side and be rationalized by lower innovation fundamentals across the EU. In this case, the US would be better at innovation than the EU and the low VC in Europe would come from the lack of good investment opportunities. However, the explanations can also come from the supply side. If investing across borders is expensive, then savings in less innovative countries cannot flow to high growth opportunities in other EU countries, which would reduce cross-border flows and supply of capital to firms. A third explanation

is that households in the EU are less willing to invest in risky assets and end up keeping savings in the form of bank deposits instead of channelling them to VCs.

To disentangle these mechanisms, I develop a multi-country endogenous growth model in which entrepreneurs require external finance to undertake R&D, and competitive venture capitalists allocate household savings across destinations. Countries differ in how efficient they are at innovation, and hence have different innovation opportunities. For the same level of capital invested, some countries will have different propensities to innovate. This is meant to capture ecosystem effects that can come, for example, from a higher quality of human capital.

Countries also differ in how easy it is to invest abroad. Investors face idiosyncratic return shocks drawn from a Fréchet distribution and iceberg-style bilateral frictions that make investing abroad more costly, as in standard quantitative spatial models (Kleinman et al., 2023). When capital markets are fragmented, savings tend to remain invested domestically even when innovation opportunities are better elsewhere. Financial integration relaxes these constraints and allows savings to flow towards higher-return innovation opportunities, improving the allocation of R&D investment and raising growth.

The quantitative framework allows households to allocate wealth between a low-risk asset and venture capital equity. In this setting, cross-border financial frictions influence not only the geographic destination of investment flows but also the aggregate share of household savings directed toward innovation. This setup is motivated by the institutional environment in Europe, where high aggregate household saving rates coexist with a lower allocation of savings to equity instruments or pension funds. It allows the model to capture that even though European and American households have similar saving rates, the former store their wealth in the form of bank deposits or insurance products that do not get channelled to young firms with risky projects.

The model yields two main predictions. First, reductions in bilateral investment frictions increase cross-border VC flows and strengthen the sensitivity of funding to destination fundamentals, namely expected innovation returns and investment efficiency. Second, holding other forces fixed, lower frictions move VC and innovative activity towards high-return hubs.

To take the model to the data I first estimate the bilateral investment costs, using the gravity equation for VC flows that the model implies. VC flows depend on destination returns and origin savings, which are absorbed by destination and origin fixed effects, and on the bilateral frictions. Following the literature on international capital flows and Pellegrino, Spolaore and Wacziarg (2025) in particular, I let these frictions depend on geographical distance and on other bilateral characteristics, together with a home-bias term for each origin. VC in Europe is much more sensitive to distance than VC in the US. In separate regressions for each bloc, doubling the distance between two locations lowers investment by about 63% between EU countries and about 7% between US states,

and EU countries invest about 6.7 times more at home than in a foreign location at a given distance, against 3.0 times for US states. For the model I estimate the frictions on all locations together, with distance and border coefficients that differ by pair type. The EU distance elasticity is then about three times the US one, and cross-border flows are higher between countries that share a border or a common legal origin. The resulting round-trip cost is 1.79 between EU countries and 1.52 between US states.

Second, I invert the model to recover two fundamentals for each location. To measure innovation I merge the VC data with PATSTAT to count the patents of VC-backed firms. I choose innovation efficiency so that the model matches each location's share of these patents, and the cost of investing in VC so that it matches the VC each location supplies. Innovation efficiency is highest in California and Massachusetts, followed by the UK, Germany, France and Texas, and it is correlated with business R&D, which the inversion does not target. The participation cost is lower where funded pension assets are larger, which also lies outside the inversion. Lower VC investment in the EU therefore reflects both frictions that lower the return to investing across borders and the cost households face when investing in market-based instruments.

Third, I run four policy experiments in the 16 EU countries of the model. Lowering participation costs to the lowest level in the EU more than doubles the VC that EU investors supply, but it changes where they invest much less. The share they keep in the EU falls from 89% to 78%. Part of the new money goes to the US, and much of the rest replaces foreign investors, so VC received by EU startups rises by only 23%. Removing home bias within the EU instead reallocates EU money towards other EU countries, and it lets each dollar buy more R&D. The two policies raise EU output per worker relative to the US by 0.9% and 0.6%, closing 6% and 4% of the EU–US productivity gap in the model. Giving EU countries the distance elasticity of US states does almost nothing on its own. Together, and with a distance elasticity between EU countries equal to the one between US states, they raise it by 2.8% and close 19%. This is more than the sum of the separate effects. Without the distance change the two policies close 18%, against 10% for their sum, since one policy raises the amount of EU money and the other sends more of it to other EU countries, where it buys more R&D. The policies also differ in who gains: lower participation costs mostly help high-cost countries and concentrate VC supply in Germany and France, while lower home bias spreads supply more widely and lowers VC received in some countries, such as Poland and Hungary.

Finally, I measure how much of the gap reflects fundamentals. Raising EU innovation efficiency and adoption to their US means closes more than half of the gap, most of it through efficiency. This puts the policies in perspective: integration and participation reforms matter, and their effects are larger together, but a larger part of the gap in the model reflects how productive research is in the EU.

Literature Review. This paper connects to several strands of the literature. First, it relates to work on endogenous growth, innovation, and knowledge spillovers (Grossman and Helpman, 1991; Jaffe, Trajtenberg and Henderson, 1993; Keller, 2002; Aghion and Howitt, 2005; Acemoglu and Cao, 2015; Akcigit and Kerr, 2018; Kerr and Robert-Nicoud, 2020; Moretti, 2021; Bergeaud et al., 2022; Berkes, Manysheva and Mestieri, 2022; Bergeaud and Verluise, 2022), in particular to the work of Howitt (2000) and Aghion, Howitt and Mayer-Foulkes (2005) on financial development and convergence clubs.

Second, it contributes to the literature on financial integration and growth (Matsuyama, 2004; Broner and Ventura, 2016; Cole, Greenwood and Sanchez, 2016; Benigno, Fornaro and Wolf, 2025; D'Amico and Alekseev, 2025). Martin and Rey (2004) model asset trade with cross-border transaction costs and imperfect substitution between assets. Recent papers have studied how bilateral frictions shape capital flows and growth (Kleinman et al., 2023; Capelle and Pellegrino, 2025; Pellegrino, Spolaore and Wacziarg, 2025; D'Amico and Alekseev, 2025). A close contribution with an endogenous growth model is Akcigit et al. (2024), who focus on cross-border corporate venture capital financing and how foreign financing can affect national security. Instead, I focus on how financial integration can give rise to a diversification motive and how barriers to cross-border investment can act as a source of misallocation in the European Union.

This paper builds on previous work on spatial models of entrepreneurial activity and venture capital by Chatterji, Glaeser and Kerr (2014), Kleinman, Liu and Redding (2023), Kerr and Robert-Nicoud (2020) and Moretti (2021). Chen and Ewens (2025) provide evidence for this channel: a US rule change that reduced the supply of capital to VC funds lowered start-up financing and led start-ups to move out of the affected states. Relative to this literature, my contribution is to embed bilateral venture capital frictions into a multi-country endogenous growth framework, allowing financial integration to affect both aggregate growth and the spatial allocation of innovation.

Finally, this work contributes to the empirical and theoretical literature on venture capital and growth (Kortum and Lerner, 2000; Bernstein, Giroud and Townsend, 2016; Akcigit et al., 2022; Greenwood, Han and Sanchez, 2022; Lerner et al., 2024; Akcigit et al., 2024; Karlsen et al., 2024; Keuschnigg, 2004; Lerner and Nanda, 2020; Jovanovic and Szentes, 2013). Opp (2019) introduces endogenous growth and venture capital in a closed economy setting, while Ewens and Farre-Mensa (2020) study empirically the effect of integration policies in private equity markets but with a focus on the US.

Roadmap. Section 2 documents the empirical facts. Section 3 presents the model and its balanced growth path, and discusses its predictions for autarky and integration. Section 4 estimates the spatial frictions. Section 5 quantifies the model and recovers the location fundamentals. Section 6 reports the counterfactual experiments. Section 7 concludes.

2 Empirical evidence

This section presents stylized facts on venture capital and private equity investment, target and investor agglomeration, and measures of integration between EU countries. Measures for the EU are compared to measures for the US for two reasons. First, the US has a dynamic VC ecosystem that supports the creation of innovative start-ups and their growth. Second, the literature has shown that venture capital investments are influenced by geographical proximity even in the US[1]. This suggests that reductions in regulatory and information frictions in the EU could reduce the fragmentation of the EU venture capital market, but that some barriers to cross-border investment might persist.

2.1 Data

Venture Capital and Private Equity. The main source of data is the Private Equity and Venture Capital module dataset of the LSEG Workspace provided by the London Stock Exchange Group. The database is the former VentureXpert provided by Refinitiv Eikon and has been used extensively in the literature (Akcigit et al., 2024). It contains information on private equity and venture capital financing rounds, including the profiles of investees, investors and the funds involved in the transaction.

In VentureXpert, investors are the venture capital firms (or general partners) managing the funds that invest in start-ups. These funds raise capital from limited partners (LPs), such as pension funds, endowments and other institutional investors. In the model section, VCs will act as financial intermediaries between households, who supply capital, and entrepreneurs, who require financing to innovate.

I define a deal as one financing round. Each financing round typically involves one target firm and one or multiple investor firms. This implies that each deal might have multiple disbursements, where a disbursement corresponds to the participation of each investor in the financing round. Unlike in other datasets, LSEG provides information on the amount each investor contributed to the round. Each observation is then a disbursement from one investor firm to a target firm.

There are different investment stages within the venture capital and private equity module, and deals are categorised depending on whether they finance young, mature or publicly traded firms. In the baseline sample I focus on investment stages that finance the formation and growth of private firms: Seed, Early stage, Later Stage and Expansion. LSEG also classifies investor firms by organizational type. I exclude disbursements associated with investors classified as Government Affiliated Programs or University Programs.

I collect information on the city and country of the headquarters of targets and investors, the date in which the deal took place, the investment stage, and the amount

[1] See Bernstein, Giroud and Townsend (2016).

invested by each firm. I then construct the bilateral investment matrices by aggregating positive investor equity total values by investor location, investee location, and year. The advantage of using a deal level dataset is that I can pin down the city where the targets and investors are located. This allows me to look at investment flows between US states and use the level of integration between US states as a benchmark for integration in the EU. Therefore, the level of analysis will be at the country level for the European Union and the rest of the world, but at the state level for the US.

LSEG also reports which fund was used by the investor firm in the deal. I choose to use the headquarters location of the investor firm instead of the location of the fund because the decision on which startup to invest is taken at the GP level. The goal is also to avoid some issues highlighted by the work of Beck et al. (2024) on "onshore offshore financial centres". To check whether this choice matters, I rebuild the bilateral matrix assigning each disbursement to the location of the fund whenever LSEG records one. The composition of investment received by EU27 startups is almost unchanged.

Innovation outcomes and patent data. I use patent data as a proxy for innovation outcomes of VC-backed firms. Data on patents is retrieved from PATSTAT Global (Autumn 2025 edition), which is the patent statistical database of the European Patent Office (EPO). PATSTAT data is extracted from the EPO worldwide bibliographic database (DOCDB) and contains bibliographical and legal event patent data. I collect data on patent filing years, inventor and applicant locations, citations, patent families and the International Patent Classification (IPC) class.

I merge PATSTAT data with the LSEG startup data using a direct matching procedure and a fuzzy-matching algorithm based on the name, location and founding date of the firm. More details on the matching procedure can be found in appendix B.3. I count the patents filed in 2000-2019 by firms whose first VC round in LSEG is in 1995 or later, whether they are filed before or after that round, and I assign each firm to the location of that round. I exclude incumbents. The merge is done for VC-backed firms in the EU27, the UK, Norway, Switzerland and the US.

2.2 Evidence

Panel a of Figure 1 shows the average annual investment received by target location as a share of GDP between 2000 and 2024. In this period, the average value of VC/GDP received by the US was 5 times larger than the one received by the EU. However, VC intensity is quite heterogeneous within the US and the EU. VC intensity is high in states like California and Massachusetts, with the hubs of Silicon Valley and Boston. In the EU, it is higher in Estonia and Sweden, countries that saw the creation of companies like Skype and Spotify, respectively. It is much lower in Southern European countries.

Panel a of Figure 1 measures VC received, which assigns each investment to the location of the startup. The same investment can also be assigned to the location of the investor's headquarters, which I call VC invested. Panel b of Figure 1 shows VC invested as a share of the location's GDP. Over 2000–2024, investors in the US invested 0.32% of US GDP per year and investors in the EU27 invested 0.05% of EU GDP. The gap is therefore as large on the investor side as on the startup side. VC invested is also very heterogeneous within each block. In the US it is concentrated in California, Massachusetts and New York, and in the EU it is higher in Estonia, Sweden and Denmark. Cyprus, Luxembourg and Malta stand out because several investment firms and their holding entities are registered there, not because they have many startups.

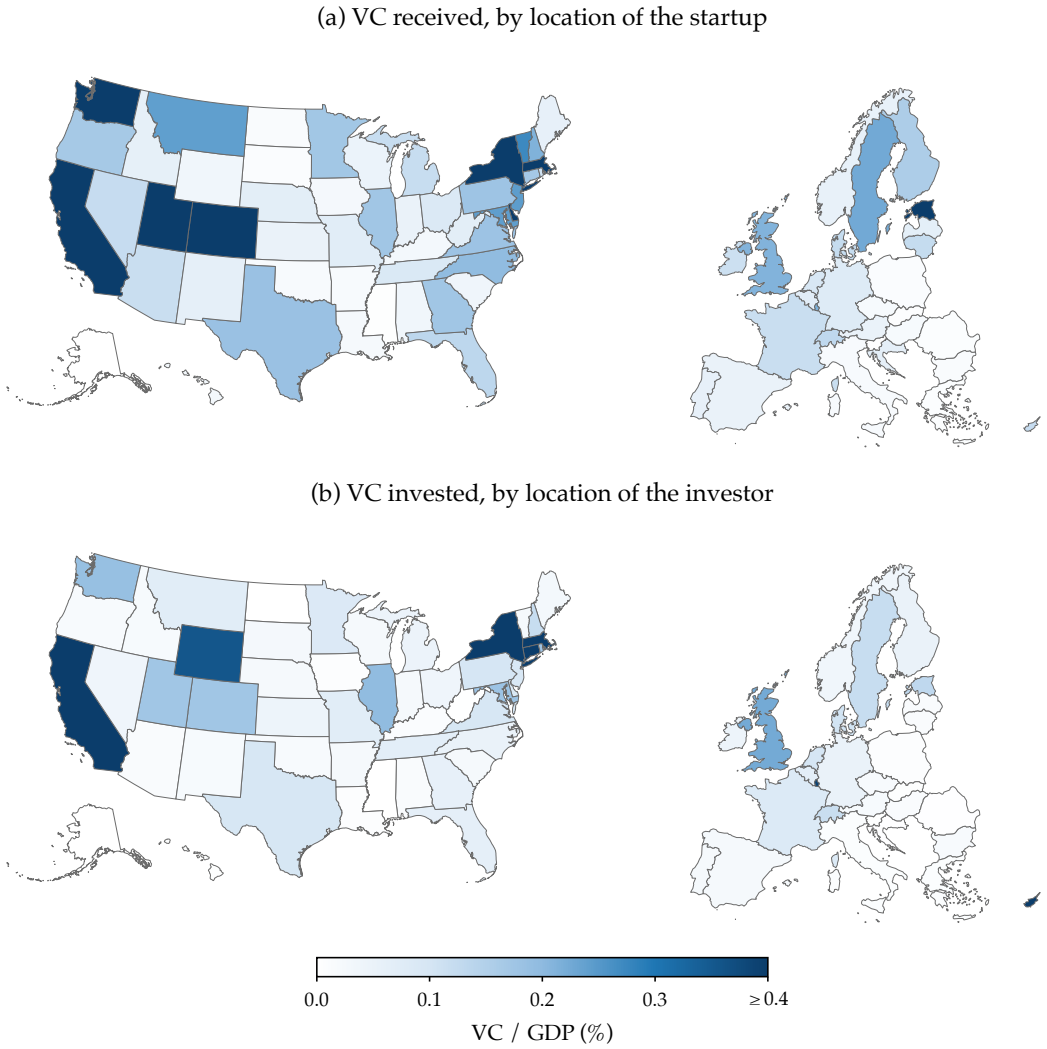
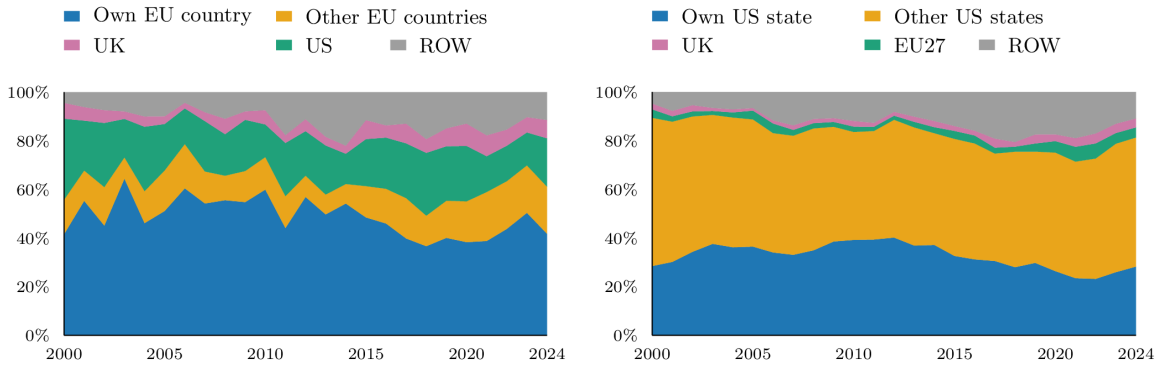


Figure 1: VC received and VC invested relative to GDP

Notes: LSEG financing rounds, 2000–2024. The sample retains Seed, Early Stage, Later Stage, and Expansion rounds and excludes government-affiliated and university-program investors. Both panels use the same colour scale. VC received is investment in startups located in the US state or country. VC invested is investment made by investors headquartered there, in startups anywhere in the world, and excludes investors recorded as "Undisclosed Firm" and investments with no investor location. Both are mean annual values divided by the location's mean annual GDP.



a) EU27 Investors b) US Investors

Figure 2: Investment shares by destination, 2000–2024

Notes: LSEG financing rounds, 2000–2024. The sample retains Seed, Early Stage, Later Stage, and Expansion rounds and excludes government-affiliated and university-program investors.

The EU differs not only in how much VC it receives, but also how it allocates its investments. Figure 2 plots annual destination shares for EU27 and US investors from 2000 to 2024. US investors allocate a large share to other US states, while investment by EU27 investors in their own countries remains substantial. The UK and transatlantic destinations also account for portions of outward investment from both blocks.

Figure B.6 in Appendix B.4.2 reports the corresponding investor-source shares for EU27 and US targets from 2000 to 2024. US investors account for a visible share of funding received by EU27 targets, whereas the share from EU27 investors in funding received by US targets is smaller.

2.3 Agglomeration

Chen et al. (2010) find that US VC is more localized than entrepreneurship and than the financial services industry, and that VCs located in the main centres outperform others. Carlino and Kerr (2015) review the evidence on agglomeration and innovation, and Rosenthal and Strange (2001) find that in US manufacturing, knowledge spillovers raise agglomeration only at the zip code level, while labour market pooling raises it at all levels of geography. Chatterji, Glaeser and Kerr (2014) have shown that venture capital in the US tends to be more concentrated than patents and GDP, which can be interpreted as VC benefiting more from agglomeration effects than innovation and production. Instead of looking into the universe of patents like the authors do, I focus instead on the patents of VC-backed firms. The universe of patents captures the patenting behaviour of large incumbents, which might be located in different regions than startups are. Differences between the weight of VC and VC-backed patents can also be an indicator of differences in the patenting behaviour of firms in different regions. This will be important in the model to understand differences across countries in patents per dollar.

Figure 3 compares VC shares with the VC-backed patenting and GDP shares across

US states and EU countries for the period of 2000-2019. The degree of agglomeration in VC is higher in the United States. California, New York, and Massachusetts together absorb 69% of US VC. California alone captures 49% of VC and 58% of VC-backed patents, compared to 13% of GDP. Unlike in Chatterji, Glaeser and Kerr (2014), VC does not seem to be more concentrated than the patenting of the firms it funds. New York seems to have a lower weight of VC-backed patents compared to the share of VC its startups receive. This might come from the fact that startups in New York belong to sectors that patent less. In Europe VC seems to be less concentrated. The top 5 countries in the EU represent 73% of VC and 61% of GDP, while the top 5 states in the US represent 76% of VC and 35% of GDP. There are some countries who capture more VC and related patenting activity than their GDP would predict. This is the case for Sweden and Finland. Italy is the opposite. Not only does it receive a small amount of VC compared to GDP, but startups seem to patent very little. Therefore, the EU does seem to have a few hubs, which are nonetheless much smaller than California.

2.4 Discussion

The patterns of low investment in VC, low cross-border flows and low agglomeration in the EU compared to the US can come from different factors. One hypothesis is that EU firms and entrepreneurs are worse at doing innovation, and so there is no demand for funding. Another hypothesis is that the source behind the different patterns relies instead on the supply of capital: frictions prevent household savings from reaching entrepreneurs. These frictions can be present at two different stages of the pipeline between households and startups. At the first stage sit the frictions between households and venture capital investors. If EU households are more risk averse, or face higher costs of investing in capital markets, savings can end up sitting in the form of bank deposits and risk free assets which do not fund innovation. Frictions can also be at a second stage: from venture capital investors to startups. This is where cross-border frictions might play a role.

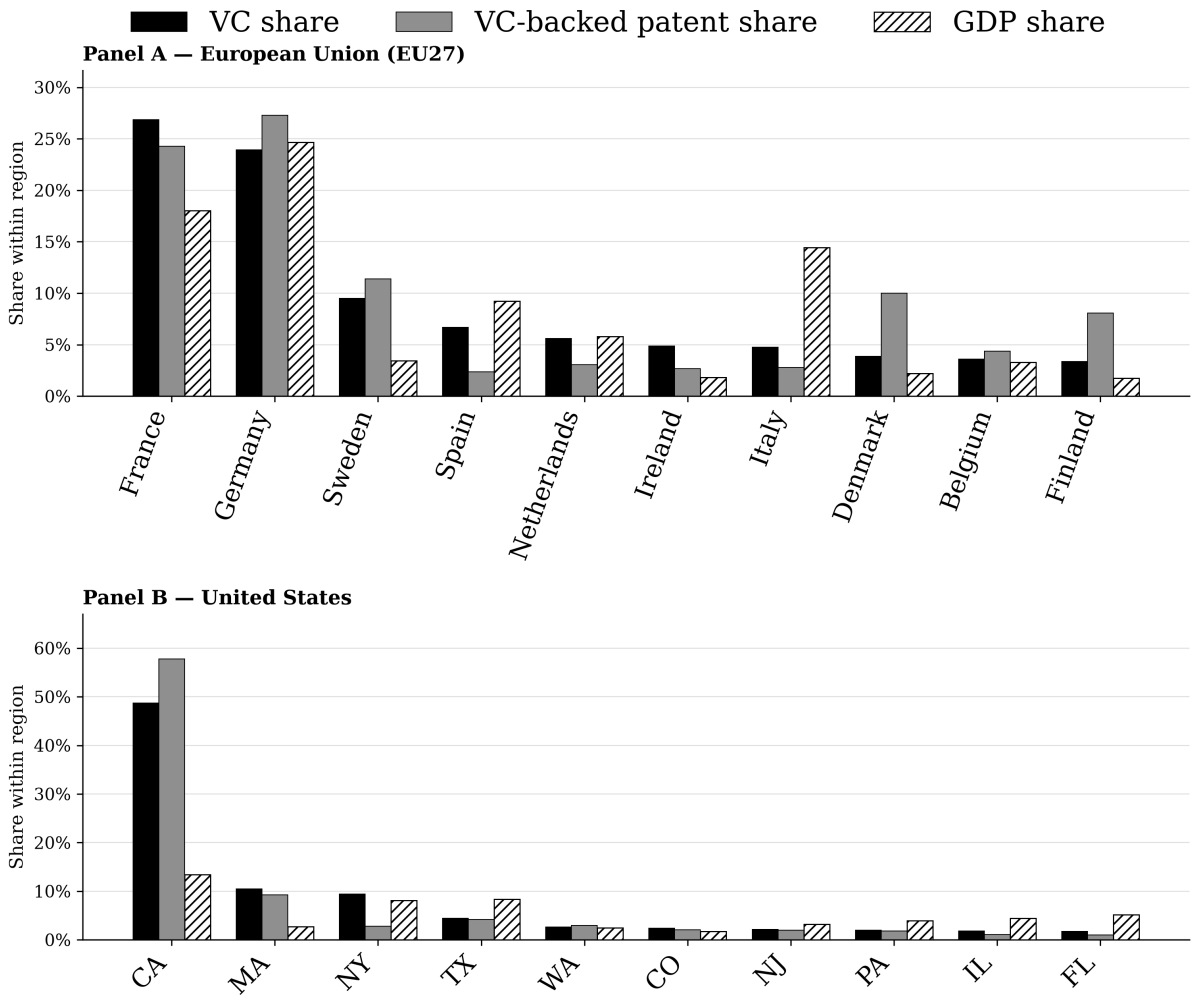


Figure 3: Spatial Concentration of VC, VC-Backed Patenting, and GDP

Notes: LSEG financing rounds, 2000-2019. The sample retains Seed, Early Stage, Later Stage, and Expansion rounds and excludes government-affiliated and university-program investors. VC shares sum positive investor-level disclosed amounts (nominal USD) by target location, including unidentified investors, and are normalized within each region. VC-backed patent shares use patents filed in 2000-2019 by firms whose first VC round is in 1995 or later, filed before or after that round, located at that round and excluding incumbents (appendix B.3). GDP shares use average GDP over 2000-2019. Panel A displays the top 10 EU27 countries by VC share, from a denominator of all 27 countries. Panel B displays the top 10 states by VC share, from a denominator of 50 states and the District of Columbia.

3 Baseline model

I develop a multi-country endogenous growth model in which households allocate their savings between physical capital and venture capital (VC). Households face country-specific costs of investing in VC, which is intermediated by domestic financial intermediaries. These intermediaries allocate funds to entrepreneurs across countries, subject to bilateral investment frictions. Entrepreneurs use VC to finance R&D, and countries differ in their efficiency at producing innovations. Successful innovations create new patents and replace incumbent firms, while productivity also grows through the adoption of technologies from the world frontier. Innovation is subject to local externalities, as past VC-funded R&D intensity increases the productivity of current research.

The model therefore links household portfolio decisions, the international allocation of VC, and productivity growth. I first describe the environment and agents' decisions, then characterize the competitive equilibrium and the balanced growth path.

3.1 Environment

Households. There are N countries indexed by i and time is discrete. Each country has a measure one of identical households with a fixed labour endowment L_i and lifetime utility

$$\sum_{t=0}^{\infty} \beta^t \log C_{it},$$

where C_{it} is consumption of the final good and $0 < \beta < 1$. Households hold two assets: domestic physical capital K_{it+1} and a one-period VC position S^v_{it+1}, intermediated by domestic financial intermediaries. Households cannot borrow or hold short positions in either asset. Capital is rented to intermediate producers at the rate r^K_{it} and has gross return

$$R^k_{it+1} = 1 - \delta_K + r^K_{it+1}.$$

A VC investment made in t finances R&D during t and pays the gross return R^v_{it+1} at the start of $t+1$, so the whole position is reinvested every period.

Holding venture capital is costly. The household pays a management fee

$$f_{it} = \frac{\varphi_i}{1+\zeta} \left(S^v_{it+1}\right)^{1+\zeta} Y_{it}^{-\zeta},$$

with $\varphi_i > 0$ and $\zeta > 0$. The parameter φ_i is country-specific and captures domestic barriers to holding venture capital, such as illiquidity, limited financial sophistication, or participation costs. It is a reduced form way of capturing that equity is more illiquid than bank deposits or government bonds, and that adjusting a portfolio tilted towards

equity is more costly (Appendix A.8.2). The budget constraint is

$$C_{it} + K_{it+1} + S^v_{it+1} + f_{it} = W_{it}L_i + R^k_{it}K_{it} + R^v_{it}S^v_{it} + D_{it},$$

where W_{it} is the wage and D_{it} are dividends from domestically-owned firms.

Production. A competitive final-good sector, with the good as numeraire, uses labour and a continuum of intermediates x^j_{it}, $j \in [0,1]$:

$$Y_{it} = L_i^{1-\alpha} \int_0^1 \left(A^j_{it}\right)^{1-\alpha} \left(x^j_{it}\right)^{\alpha} dj,$$

where A^j_{it} is the productivity of line j and $0 < \alpha < 1$. The holder of the patent on line j makes one unit of intermediate from one unit of capital. A competitive fringe can make it with μ units of capital, where $1 < \mu < 1/\alpha$. The monopolist engages in limit pricing, which is optimal under this bound.

Innovation and adoption. Following Eaton and Kortum (1996) and Liu and Ma (2021), countries differ in aggregate productivity and also in technology within the same line. This reflects that innovations do not diffuse immediately across the world, or are adopted with a delay. The frontier of line j, the world frontier and country productivity are

$$\bar{A}^j_t \equiv \max_i A^j_{it}, \qquad \bar{A}_t \equiv \int_0^1 \bar{A}^j_t \, dj, \qquad A_{it} \equiv \int_0^1 A^j_{it} \, dj,$$

so $A_{it} \leq \bar{A}_t$.

Following Aghion, Howitt and Mayer-Foulkes (2005), entrepreneurs in each country and line can produce an innovation for the next period. If they invest Q^j_{it} units of the final good in research, financed by VC, they succeed with probability

$$\eta^j_{it} = \chi_i \left(\frac{Q^j_{it}}{\bar{A}^j_t}\right)^{\frac{1}{\gamma}} \left(\frac{Q_{it-1}}{Y_{it-1}}\right)^{\sigma}, \qquad Q_{it} \equiv \int_0^1 Q^j_{it} \, dj, \tag{1}$$

where $\chi_i > 0$ is R&D efficiency and $\gamma \geq 1$ governs congestion due to scarcity of talent. Scaling by $\bar{A}^j_t$ captures that research becomes harder as the frontier advances. I interpret η^j_{it} as an arrival probability over a short interval, so the chance that two countries innovate in the same line in the same period is negligible.

A successful entrant becomes the next incumbent with productivity $\kappa \bar{A}^j_t$, where $\kappa \geq 1$ is a step size common across countries. With probability $b_i \in [0,1]$ the entrepreneur does not innovate but adopts the frontier $\bar{A}^j_t$. As in Aghion, Howitt and Mayer-Foulkes (2004), adoption lets laggards benefit from innovations made elsewhere even when they do little R&D. It is country-specific, consistent with evidence that diffusion is not immediate and

depends on factors such as human capital (Keller, 2002; Cai, Li and Santacreu, 2022). Otherwise the incumbent keeps its technology:

$$A^j_{it+1} = \begin{cases} \kappa \bar{A}^j_t & \text{with probability } \eta^j_{it}, \\ \bar{A}^j_t & \text{with probability } b_i, \\ A^j_{it} & \text{with probability } 1 - \eta^j_{it} - b_i. \end{cases} \tag{2}$$

Local spillovers. The last term in (1) is a local research externality: higher past VC-funded research relative to output raises the productivity of current research. Entrepreneurs take this externality as given. The parameter $\sigma \geq 0$ measures its strength, and the externality is absent if $\sigma = 0$. I assume $1/\gamma + \sigma < 1$, so research has decreasing returns on a balanced growth path even with the externality. I use intensity and not the level so that the externality depends on how specialized a location is in VC-funded research and not on its size. The history of Silicon Valley illustrates this force. Spin-offs and job-hopping spread knowledge quickly, and successful entrepreneurs reinvested in new local companies (Saxenian, 1996).

Venture capital. Competitive VC intermediaries in country i raise S^v_{it+1} and allocate it to R&D projects in all N countries. Following Kleinman et al. (2023) and Pellegrino, Spolaore and Wacziarg (2025), returns are affected by an idiosyncratic match shock and by cross-border frictions. A continuum of intermediaries $l \in [0, 1]$ in country i draws a match quality $\phi_{int}(l)$ for each destination n, independently across destinations, from

$$F(\phi) = \exp\left(-\phi^{-\epsilon}\right), \qquad \phi > 0, \quad \epsilon > 1,$$

with the scale normalized to one. The shock captures the quality of the match between a specific fund manager and a specific startup. Some investors find good opportunities in one country and not in another, for example because of complementarities between the investor's expertise and the startup's technology. A lower ϵ means more heterogeneity across investor-destination matches and more extreme draws.

Investors also face bilateral frictions τ_{in} of the iceberg form. I normalize $\tau_{ii} = 1$. Investing abroad is usually more costly than investing at home, so $\tau_{in} > 1$ for most pairs, but the estimates in Section 4 allow $\tau_{in} < 1$. These frictions summarize factors such as regulatory barriers, information asymmetries and differences in the legal system.

3.2 Optimal behaviour

Households. The first-order conditions of the household problem are the Euler equation and the portfolio choice:

$$\frac{1}{C_{it}} = \beta \frac{R^k_{it+1}}{C_{it+1}}, \tag{3}$$

$$R^v_{it+1} = R^k_{it+1} \left(1 + \varphi_i \left(\frac{S^v_{it+1}}{Y_{it}} \right)^{\zeta} \right). \tag{4}$$

The portfolio condition states that the marginal cost of tilting the portfolio towards venture capital equals the gain from the expected VC premium.

Intermediates and profits. The monopolist sets the limit price μr^K_{it}. Demand and line profits are

$$x^j_{it} = A^j_{it} L_i \left(\frac{\alpha}{\mu r^K_{it}} \right)^{\frac{1}{1-\alpha}}, \tag{5}$$

$$\pi^j_{it} = \bar{\omega}\, A^j_{it} L_i \left(r^K_{it} \right)^{-\frac{\alpha}{1-\alpha}}, \qquad \bar{\omega} \equiv (\mu - 1) \left(\frac{\alpha}{\mu} \right)^{\frac{1}{1-\alpha}}.$$

Profits are linear in the line's technology. Aggregating across lines, with $K_{it} \equiv \int_0^1 K^j_{it} dj$,

$$Y_{it} = (A_{it} L_i)^{1-\alpha} K^{\alpha}_{it},$$

$$r^K_{it} K_{it} = \frac{\alpha}{\mu} Y_{it}, \qquad \Pi_{it} = \frac{\alpha(\mu - 1)}{\mu} Y_{it}. \tag{6}$$

Households receive the profits of incumbents net of what they pay to the VC investors that financed the patents created in the previous period:

$$D_{it} = \Pi_{it} - \rho_{it}\, Q_{it-1}. \tag{7}$$

Productivity and the frontier. Research is undirected and lines are symmetric, so in the symmetric equilibrium the innovation probability is the same in every line of a country, written η_{it}. Integrating (2) over lines gives the law of motion of country productivity, and counting the lines that are improved gives the frontier:

$$A_{it+1} = \eta_{it}\, \kappa \bar{A}_t + b_i \bar{A}_t + (1 - \eta_{it} - b_i)\, A_{it}, \tag{8}$$

$$\frac{\bar{A}_{t+1}}{\bar{A}_t} = 1 + (\kappa - 1) \sum_{n=1}^{N} \eta_{nt}. \tag{9}$$

Countries further from the frontier grow faster because they benefit more from spillovers, as in Eaton and Kortum (1996). Frontier growth is driven by innovation in all countries. Adoption changes relative productivity levels but not the growth of the frontier.

Patents and the return to innovation. An innovator obtains a perpetual patent on its line, which lasts until the next successful inventor replaces it. The entrepreneur sells the patent to domestic households, and the proceeds compensate the VC investors. An incumbent earns π_{it}^j and is replaced with probability $\eta_{it} + b_i$, so the value of a patent discounted at R_{it+1}^k is

$$V_t\left(A_{it}^j\right) = \pi_{it}^j + (1 - \eta_{it} - b_i)\,\frac{V_{t+1}\left(A_{it}^j\right)}{R_{it+1}^k}. \tag{10}$$

Since profits are linear in productivity, the value function is linear with slope v_{it}, which satisfies

$$v_{it} = \bar{\omega} L_i \left(r_{it}^K\right)^{-\frac{\alpha}{1-\alpha}} + (1 - \eta_{it} - b_i)\,\frac{v_{it+1}}{R_{it+1}^k}. \tag{11}$$

Entrepreneurs have no internal funds, so R&D is VC-financed. Competitive intermediaries are paid the marginal value of R&D, which defines the gross payoff to a marginal unit of VC in i:

$$\rho_{it+1} \equiv \frac{\partial}{\partial Q_{it}}\left[\eta_{it}(Q_{it})\,\kappa v_{it+1}\bar{A}_t\right] = \frac{1}{\gamma}\frac{\eta_{it}}{Q_{it}}\,\kappa v_{it+1}\bar{A}_t, \tag{12}$$

where $\kappa v_{it+1}\bar{A}_t$ is the value of a new patent, since a successful entrant starts at $\kappa\bar{A}_t^j$. Because η_{it} is concave in Q_{it}, ρ_{it+1} falls with aggregate funding and is pinned down jointly with VC flows in equilibrium.

Allocation of venture capital. Intermediary l chooses the destination with the highest realized payoff, given ρ_{nt+1} from (12):

$$\nu_{it+1}(l) = \max_n \left\{\frac{\phi_{int}(l)\,\rho_{nt+1}}{\tau_{in}}\right\}.$$

Using the properties of the Fréchet distribution and Kleinman et al. (2023), the share of origin i's savings allocated to n is the probability that n offers the best return:

$$z_{int} = \frac{\left(\rho_{nt+1}/\tau_{in}\right)^{\epsilon}}{\sum_{m=1}^{N}\left(\rho_{mt+1}/\tau_{im}\right)^{\epsilon}}. \tag{13}$$

Flows increase with the return ρ_{nt+1}, which rises with the host country's R&D efficiency, market size and innovation step, and fall with τ_{in}. Because shares depend on returns in all destinations, bilateral holdings depend on the whole vector of frictions $\{\tau_{im}\}$ and on

the attractiveness of alternatives. Capital may therefore not go to the countries with the best opportunities if barriers are large, so frictions act as a source of misallocation.

The expected gross VC return to origin i is

$$R^v_{it+1} = \Gamma\left(1 - \frac{1}{\epsilon}\right)\left[\sum_{n=1}^{N}\left(\frac{\rho_{nt+1}}{\tau_{in}}\right)^{\epsilon}\right]^{1/\epsilon}, \tag{14}$$

with $\Gamma(\cdot)$ the Gamma function, and it is the same in every destination. The best matches are allocated first and successive units meet progressively less suitable projects, consistent with evidence that screening and monitoring costs rise with project scale (Kaplan and Stromberg, 2001; Cole, Greenwood and Sanchez, 2016).

Financial flows and effective R&D are distinct. The observed flow from i to n is

$$\widetilde{Q}_{int} = z_{int}\, S^v_{it+1}. \tag{15}$$

Gravity equation. The model delivers a structural gravity equation for VC flows. Substituting the portfolio share (13) into the observed flow (15) gives

$$\widetilde{Q}_{int} = S^v_{it+1}\,\frac{\rho^{\epsilon}_{nt+1}\,\tau^{-\epsilon}_{in}}{\Phi_{it}}, \qquad \Phi_{it} \equiv \sum_{m=1}^{N}\left(\frac{\rho_{mt+1}}{\tau_{im}}\right)^{\epsilon}, \tag{16}$$

where Φ_{it} is the outward multilateral resistance term (Anderson and van Wincoop, 2003). Flows from i to n rise with the funding i supplies and with the return in n, and fall with the bilateral friction τ_{in} relative to the frictions i faces with all other destinations. Equation (16) is the basis for estimating τ_{in} in Section 4.

A flow handled by intermediary l, however, buys only $\phi_{int}(l)/\tau_{in}$ units of effective R&D per unit. Destination effective R&D is

$$Q_{nt} = \sum_{i=1}^{N}\int_0^1 \frac{\phi_{int}(l)}{\tau_{in}}\,\widetilde{Q}_{int}(l)\,dl,$$

and the zero-profit condition states that payments to the VC investors who finance innovation in n equal the marginal value their funding generates:

$$\rho_{nt+1}\,Q_{nt} = \sum_{i=1}^{N} z_{int}\, S^v_{it+1}\, R^v_{it+1}. \tag{17}$$

Appendix A.3 derives (13), (14) and (17).

3.3 Competitive equilibrium

Given initial technologies, capital and VC intensity, fundamentals $\{L_i, \chi_i, b_i, \varphi_i, \tau_{in}\}$ and parameters $\{\beta, \alpha, \mu, \delta_K, \zeta, \gamma, \sigma, \kappa, \epsilon\}$, a competitive equilibrium is a sequence of allocations and prices such that in every period households satisfy (3) and (4), producers and patent holders satisfy (5) and (11), capital demand equals household holdings, innovation and productivity follow (1), (8) and (9), VC intermediaries satisfy (13) and (17), and the world goods market clears:

$$\sum_{i=1}^{N} Y_{it} = \sum_{i=1}^{N} \left[C_{it} + K_{it+1} - (1-\delta_K) K_{it} + S^v_{it+1} + f_{it} \right]. \tag{18}$$

The system forms a loop. The returns ρ_{nt+1} and the frictions τ_{in} set where VC goes, VC received sets innovation, and innovation feeds back into ρ_{nt+1} through the value of a patent. Appendix A.4 lists all conditions.

3.4 Balanced growth path

On a balanced growth path (BGP) the world frontier grows at a constant gross rate g. For any variable X_{it} define $x_{it} \equiv X_{it}/\bar{A}_t$, and let $a_i \equiv A_i/\bar{A}$ be relative productivity.

Growth and the productivity gap. Dividing (8) by the frontier in $t+1$ gives the law of motion of the gap (Appendix A.2), whose steady state is

$$g = 1 + (\kappa - 1) \sum_{n=1}^{N} \eta_n, \qquad a_i = \frac{\eta_i \kappa + b_i}{g - (1 - \eta_i - b_i)}. \tag{19}$$

Growth is set by innovation in all countries, while the gap is set by individual R&D efforts. A lower η_i relative to g means a larger distance from the frontier. When b_i is high laggards catch up more quickly, and when it is low a country relies more on its own technology.

Return to VC. The Euler equation implies a common return to capital and rental rate,

$$R^k = \frac{g}{\beta}, \qquad r^K = \frac{g}{\beta} - 1 + \delta_K. \tag{20}$$

Normalizing (12) and solving (11),

$$\rho_n = \frac{\kappa}{\gamma} \frac{\eta_n}{q_n} v_n, \qquad v_n = \frac{\bar{\omega} L_n \left(r^K\right)^{-\frac{\alpha}{1-\alpha}}}{1 - (1 - \eta_n - b_n)\beta/g}, \tag{21}$$

where q_n is VC-funded R&D normalized by the frontier. For given q_n the return rises with R&D efficiency and market size and falls with the replacement rate $\eta_n + b_n$, which

shortens the life of a patent. Relative productivity a_n does not enter, because a successful entrant starts at the frontier of its line. On the BGP VC intensity is constant, so

$$\eta_n = \chi_n \, q_n^{1/\gamma} \left(\frac{q_n}{y_n} \right)^{\sigma}.$$

Holding y_n and v_n fixed, η_n rises with q_n with an elasticity below one, since $1/\gamma + \sigma < 1$, so ρ_n falls with q_n. Because the externality is not internalized, the social return to a unit of VC is

$$\rho_n^S = (1 + \beta\gamma\sigma) \, \rho_n, \tag{22}$$

since an additional unit of R&D also raises the productivity of next period's research (Appendix A.6).

VC allocation and participation. Shares and returns on the BGP are (13) and (14) with ρ_n from (21). Normalizing (17), destination payments satisfy

$$\rho_n \, q_n = g \sum_{i=1}^{N} z_{in} \, R_i^v \, s_i^v.$$

The left side equals $(\kappa/\gamma)\eta_n v_n$, so VC investors are paid a share $1/\gamma$ of the normalized value of the patents created in n. VC inflows into a destination are pinned down by the value of the patents it creates and by the returns that origins require. Combining (20) with (4),

$$\varphi_i \left(\frac{g \, s_i^v}{y_i} \right)^{\zeta} = \frac{R_i^v}{R^k} - 1. \tag{23}$$

The VC return exceeds the return on capital by a participation wedge that rises with φ_i and with VC over GDP, so VC returns differ across countries even on the BGP.

Gravity. On the BGP, the gravity equation (16) becomes

$$\widetilde{Q}_{in} = S_i^v \, \frac{\rho_n^{\epsilon} \, \tau_{in}^{-\epsilon}}{\Phi_i}, \qquad \Phi_i \equiv \sum_{m=1}^{N} \left(\frac{\rho_m}{\tau_{im}} \right)^{\epsilon}. \tag{24}$$

Section 4 takes this equation to the data to estimate τ_{in} given an external ϵ.

3.5 Model discussion

The model speaks to the facts in Section 2. Bilateral frictions make VC home-biased and sensitive to distance. Differences in innovation efficiency and the local spillover shape where VC and innovation concentrate, and participation costs shape how much VC each location supplies.

Financial integration works through two margins. The geographic allocation margin is how lower frictions change z_{in} for a given VC supply. The participation margin is how changes in R_i^v change VC supplied relative to GDP.

Autarky. When τ_{in} goes to infinity for $i \neq n$, all VC is invested at home. This does not mean all savings finance innovation, since households still choose between capital and VC through (23). A location with weak innovation opportunities or high φ_i invests little in VC even in autarky.

Complete financial integration. If all frictions are removed, every origin faces the same menu and

$$z_{in} = z_n = \frac{\rho_n^\epsilon}{\sum_{m=1}^N \rho_m^\epsilon}.$$

Origins still supply different amounts of VC because s_i^v depends on participation costs and income. Destinations with high marginal returns attract more VC, but extra funding lowers ρ_n through congestion, so integration can raise the concentration of innovation without complete spatial concentration.

Trade-offs. Integration affects growth through two channels. Lower frictions raise the effective R&D bought by each unit of funding, which can raise growth even in a symmetric world. Integration also reallocates funding across destinations. This reinforces the first channel when capital moves to destinations with a high marginal contribution to frontier growth, and offsets it when private and social returns differ. Integration therefore does not mechanically improve the spatial allocation of R&D.

Two further forces limit what a location or bloc gains. First, more VC supplied by its own households lowers returns at home, so it can replace foreign investors, and VC received rises by less than VC invested. Second, relative productivity depends on innovation relative to frontier growth, as in (19). Faster frontier growth can therefore lower relative productivity in a location even when its innovation rises.

3.6 Discussion of assumptions

There are two key assumptions in the model. The first one is that households invest in VC only through intermediaries located where they live. In the estimation of the model, I assume this holds at the country level in the EU, but also at the state level in the US. The dataset only registers where the VC firm is located, but not where the investors in its funds are, so I cannot pin down the share of funding that comes from domestic and foreign households. However, the literature provides some evidence of home bias in the allocation of capital to VC funds. Regarding the US, Hochberg and Rauh (2013) show that public pension funds tend to invest disproportionately in funds from their own

state, particularly in VC. This suggests that investor location and VC manager location are correlated, although it does not imply that all funding is domestic. When it comes to the EU, cross-border fundraising has historically faced different national regulatory requirements. The AIFMD and EuVECA passport regimes introduced in 2013 facilitated cross-border marketing of investment funds, although differences in national regulation and taxation remain.

The second key ingredient is that the cost of investing in VC differs across locations. This is motivated by differences in the institutions that channel savings into VC across EU countries and US states. In the US, many rules are federal, but pension fund arrangements and investment policies differ across states. Gompers and Lerner (1998) show that VC fundraising responds to changes in pension investment restrictions, both at the aggregate and at the state level. Chen and Ewens (2025) also show that restrictions on banks' investments in VC affect regional VC funding and startup activity. In the EU, countries differ substantially in the extent to which they rely on pay-as-you-go pension systems compared to funded occupational and private pension arrangements. These differences can affect the amount of savings channelled towards VC and the costs of accessing this asset class.

4 Measuring Spatial Frictions in Venture Capital

To take the model to the data, I need to estimate the cross-border frictions τ_{in}. Investors in most locations keep a very large share of their portfolio at home, as the diagonals of Figures B.4 and B.5 in the appendix show. This pattern suggests that investing outside the home location may carry an additional cost beyond those associated with the characteristics of each pair. To allow for this, I write τ_{in} as the product of a border-effect term h_i, which applies to all investments from origin i outside its own location, and a bilateral term $\tilde{\tau}_{in}$, which depends on the characteristics of the pair.

$$\tau_{in} = h_i \, \tilde{\tau}_{in} \quad \text{for } i \neq n, \qquad \tau_{ii} = 1. \tag{25}$$

Following the literature on international flows and Pellegrino, Spolaore and Wacziarg (2025) in particular, I assume the bilateral iceberg-style costs $\tilde{\tau}_{in}$ are a function of geographical distance, and of other bilateral characteristics identified in the literature of international finance and venture capital investment. Geography seems to be particularly important for VC because investors monitor their portfolio companies in person. Bernstein, Giroud and Townsend (2016) show that new direct flights that cut investors' travel time to their existing portfolio companies raise innovation and the likelihood of a

successful exit at those companies. Let x_{in} collect these variables, and

$$-\epsilon \ln \tilde{\tau}_{in} = x'_{in}\beta \qquad \eta_i = \epsilon \ln h_i. \tag{26}$$

Therefore, to recover the matrix of τ_{in}, I need the values of the variables in x_{in}, and estimates for the vectors β, η_i and the parameter ϵ. I take the value of ϵ from Kleinman et al. (2023), and estimate β and η_i using the gravity equation derived from the model.

By taking the log of the gravity equation (16), the venture capital flow $\widetilde{Q}_{int}$ from origin i to destination n in year t is

$$\ln \widetilde{Q}_{int} = \underbrace{\ln S^v_{it} - \ln \Phi_{it}}_{\alpha_{it}} + \underbrace{\epsilon \ln \rho_{nt+1}}_{\delta_{nt}} - \epsilon \ln \tau_{in}.$$

where S^v_{it} is total funding supplied by i. The origin-year term α_{it} absorbs total VC supply and outward multilateral resistance, and the destination-year term δ_{nt} absorbs expected returns and other destination characteristics. Substituting (25) and (26) gives the gravity equation to be estimated:

$$\ln \widetilde{Q}_{int} = \alpha_{it} + \delta_{nt} + \mathbf{1}\{i \neq n\} \left[x'_{in}\beta - \eta_i\right]. \tag{27}$$

The term $-\eta_i$ is estimated as a coefficient on an origin-specific foreign dummy, and measures how much less origin i invests in any foreign location than at home, conditional on the bilateral variables. The vector β measures how bilateral characteristics shift investment across foreign destinations.

I write τ as a function of observables, and do not invert it pair by pair from observed flows as in Novy (2013), for two reasons. A first reason is coverage. The inversion needs positive flows in both directions and within both locations, which holds for only 869 of the 2,775 pairs (Appendix C), while the model needs a friction for every pair. A second reason is that a function of observables lets me change specific terms in the counterfactuals, such as the EU home effect or the EU distance slope.

Home bias and sensitivity to distance. The main empirical question is whether bilateral frictions are stronger within Europe than within the United States. In particular, I want to test whether home bias and geographic distance are more important barriers to VC investment across European countries than across US states. To answer this question I start by estimating the coefficient on distance on separate samples - one for EU countries and another for US states. For origin i, destination n and year t,

$$\mathbb{E}[\widetilde{Q}_{int}] = \exp\left(\alpha_{it} + \delta_{nt} + \beta_d \log d_{in} - \eta\, \mathbf{1}\{i \neq n\}\right), \tag{28}$$

where $\widetilde{Q}_{int}$ is disclosed VC investment (USD millions, Seed through Later stage) from investors in i to startups in n, excluding government-affiliated and university-program investors, α_{it} and δ_{nt} are origin-year and destination-year fixed effects, d_{in} is distance and η is a home effect common to all origins. Following Silva and Tenreyro (2006) and Head and Mayer (2014), I estimate this gravity equation in levels using Poisson Pseudo-Maximum Likelihood (PPML) to account for zero-flows. In this case, domestic observations are retained because they identify the foreign-versus-home margin. The equation is estimated for 2000-2019. Standard errors are clustered by directed pair.

Table 1: Home bias and distance: EU and US estimated separately

	(1) EU countries	(2) US states and DC
Log distance	-1.451^{***}	-0.098^{**}
	(0.140)	(0.044)
Home	1.900^{***}	1.093^{***}
	(0.196)	(0.160)
Locations	27	51
Observations	8,251	42,605
Origin × year FE	Yes	Yes
Destination × year FE	Yes	Yes

Notes: PPML estimates of equation (28) on disclosed VC amounts, 2000-2019. Distance applies to all pairs, with internal distance for domestic pairs. Column (1) uses flows among EU27 countries and (2) among US states and DC. Pairs with zero flows in every year are kept. Observations exclude cells whose origin or destination has no VC in that year, and cells separated by the fixed effects. Standard errors clustered by directed pair in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Distance is a much stronger barrier to VC within the EU than within the US. In the EU, doubling the distance between two countries lowers investment by about 63%. Between US states the same change lowers it by about 7%. European investors are also more home-biased. Holding distance fixed, an EU country invests about 6.7 times more at home than in another European location, against 3.0 times for a US investor investing in a different state.

Within EU frictions. Different factors influence the behaviour of VC investors beyond distance. To measure which bilateral characteristics shape where cross-border investment goes, I drop domestic pairs and estimate on EU27 cross-border flows only:

$$\mathbb{E}[\widetilde{Q}_{int}] = \exp\left(\alpha_{it} + \delta_{nt} + x'_{in}\beta\right), \qquad i \neq n, \tag{29}$$

where x_{in} contains log distance, a common land border, common legal origin and cultural distance. Cultural distance and the border come from Pellegrino, Spolaore and Wacziarg (2025). Common legal origin follows the classification of La Porta, Lopez-de Silanes and Shleifer (2008).

Table 2: EU bilateral frictions: cross-border flows only

	(1)	(2)	(3)	(4)
Log distance	-1.424^{***}	-1.150^{***}	-1.209^{***}	-0.998^{***}
	(0.156)	(0.159)	(0.165)	(0.169)
Common border	0.253	0.268	0.250	0.271
	(0.180)	(0.172)	(0.170)	(0.166)
Common legal origin		0.515^{***}		0.423^{***}
		(0.125)		(0.123)
Cultural distance (std.)			-0.473^{***}	-0.423^{***}
			(0.095)	(0.097)
Observations	5,340	5,340	5,340	5,340
Origin × year FE	Yes	Yes	Yes	Yes
Destination × year FE	Yes	Yes	Yes	Yes

Notes: PPML estimates of equation (29) on cross-border flows among EU27 countries, disclosed VC amounts, 2000–2019. Domestic pairs are excluded. Every column includes a common-border dummy. Cultural distance is standardized (mean 0, SD 1). Pairs with zero flows in every year are kept. Observations exclude cells whose origin or destination has no VC in that year, and cells separated by the fixed effects. Standard errors clustered by directed pair in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Bilateral characteristics beyond geography shape where European VC goes. Countries with a common legal origin invest about 53% more in each other, and a one-standard-deviation increase in cultural distance lowers investment by about 35%. Once these variables are included, the distance coefficient falls from -1.42 to -1.00, so part of what appears as a distance effect reflects institutional and cultural proximity between neighbouring countries. A common border has no additional effect.

Bilateral frictions τ for the model. The model needs τ_{in} for every pair of locations, including transatlantic pairs. The results in table 1 show that investment in the EU is more sensitive to geographical distance than in the US. Therefore, I let the distance and border coefficients differ by pair type r: flows between EU countries, flows between US states, and all other pairs. I estimate on flows among 81 locations, the 27 EU countries, the United Kingdom, Norway, Switzerland, the 50 US states and the District of Columbia, over 2000–2019, the same window as Tables 1 and 2.[2] I include them because they are large sources of VC for EU startups. Their flows to and from EU countries provide additional observations for the fixed effects of EU locations, which are then estimated from a broader set of partners. The slopes for EU pairs are estimated on EU pairs only, while their fixed effects use all partners:

$$\mathbb{E}[\widetilde{Q}_{int}] = \exp\Big(\alpha_{it} + \delta_{nt} + \mathbf{1}\{i \neq n\}\big[x'_{in}\beta_r - \eta_i\big]\Big), \tag{30}$$

[2]Croatia, Malta, Slovenia, Alaska, North Dakota and Wyoming have no domestic VC flows in 2000–2019, so their home-bias terms are not identified and the friction matrix covers 75 locations. None of the six is among the 62 locations of the model (Appendix D.1).

where x_{in} contains $\log(d_{in}/d_{ii})$ and a common border for every pair type r, plus common legal origin and cultural distance for EU pairs, d_{ii} is the internal distance of origin i, and η_i is origin i's home-bias term. This generalizes the common home effect in (28) to one home-bias term per origin. Legal origin and cultural distance do not vary across US states, so they cannot be separated from the US home effects. Appendix C defines the variables.

Table 3 reports the estimates. Distance lowers investment for every pair type, and more between EU countries than between US states, with coefficients of -0.41 and -0.15. A common border and a common legal origin also raise investment between EU countries. Once these are included, cultural distance is no longer significant. The EU distance coefficient is smaller than in Table 2, which uses the same years, because here each location has one origin and one destination effect across all partners, as in the model, while in Table 2 these effects come from EU partners only. The estimate I use for τ is therefore a conservative measure of the EU-US gap. Appendix C reports the remaining coefficients and tests.

Recovering τ. With $\epsilon = 10$,

$$\tau_{in} = \exp\big[(\eta_i - x'_{in}\beta_r)/\epsilon\big], \qquad i \neq n, \qquad \tau_{ii} = 1. \tag{31}$$

The home level of each origin's frictions therefore comes from the regression.[3] Because h_i is estimated from domestic flows, the domestic shares of the model are partly targeted, even though they are not targeted when the model is solved. The regression identifies one home effect per location but does not say whether it belongs to the investor or to the destination. I assign it to the investor, and report the round trip $\sqrt{\tau_{in}\tau_{ni}}$, which does not depend on that choice. The average round trip is 1.79 between EU countries, 1.52 between US states and 1.87 between EU countries and US states.

Robustness. The estimated round trips are close to those inverted directly from observed flows. Weighted by flows, they are within about 1% for pairs between EU countries, between US states, and between EU countries and US states, and the log correlation across pairs is 0.71. The coefficients are stable when I add ten other bilateral variables and when I estimate on five-year windows from 2000 to 2024. The EU distance coefficient is larger in absolute value than the US one in every specification. Appendix C reports these checks.

[3] Since h_i is estimated, τ_{in} can fall below one when an origin invests less at home than in a foreign location at the same distance. Among the 62 locations of the model this is the case only for Delaware and Rhode Island, with h_i of 0.95 and 0.97. Their frictions are below one for 37 of the 3,782 pairs, and the lowest value is 0.96.

Table 3: Estimating τ: pooled gravity with home effects

	(1) Distance	(2) + Legal origin	(3) + Culture	(4) Baseline
Log relative distance, EU–EU	-0.324^{***}	-0.437^{***}	-0.300^{***}	-0.412^{***}
	(0.076)	(0.074)	(0.077)	(0.081)
Log relative distance, US–US	-0.157^{***}	-0.154^{***}	-0.156^{***}	-0.145^{***}
	(0.028)	(0.028)	(0.028)	(0.036)
Log relative distance, other pairs	-0.448^{***}	-0.437^{***}	-0.445^{***}	-0.414^{***}
	(0.021)	(0.020)	(0.021)	(0.024)
Common legal origin, EU–EU		1.173^{***}		0.984^{***}
		(0.142)		(0.123)
Cultural distance (std.), EU–EU			-0.271^{**}	-0.115
			(0.117)	(0.093)
Common border, EU–EU				0.595^{***}
				(0.128)
Common border, US–US				0.019
				(0.106)
Common border, other pairs				0.343^{*}
				(0.189)
Locations	81	81	81	81
Observations	98,991	98,991	98,991	98,991
Pseudo-R^2	0.984	0.984	0.984	0.984
Origin home effects	Yes	Yes	Yes	Yes
Domestic pairs	Included	Included	Included	Included
Origin × year FE	Yes	Yes	Yes	Yes
Destination × year FE	Yes	Yes	Yes	Yes

Notes: PPML estimates of equation (30) on flows among 27 EU countries, the UK, Norway, Switzerland, 50 US states and DC, including domestic flows, disclosed VC amounts, 2000–2019. Government-affiliated and university-program investors excluded. One home effect per origin (not shown). Other pairs: transatlantic, UK and Norway/Switzerland pairs. Bilateral terms are zero on domestic pairs. Cultural distance standardized over EU–EU pairs. Pseudo-R^2: squared correlation of observed and fitted flows. Standard errors clustered by directed pair in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5 Model Estimation

I quantify the model with data on bilateral VC investment, patents, citations and national accounts. Some parameters are set externally or come directly from the data. I set two adoption parameters with the help of indirect inference. I then choose two location-specific fundamentals, innovation efficiency and the participation cost, so that the model exactly matches each location's patents and the VC it supplies.

The model has 62 locations: 16 EU countries, the United Kingdom and 45 US states.[4] The 16 locations I leave out have 0.09% of VC-backed patents and 1.3% of VC flows in the EU27, the UK and the 50 US states (Appendix D.1). The model has no rest of the world, so it matches the VC flows between these 62 locations, which are 74% of the total VC they receive.

Inputs are annual means over 2000–2019, because the model describes a balanced growth path rather than a particular year. I end the window in 2019 because I count granted patent families in the year they were first filed, and grants take several years. Families first filed in 2022 and 2023 are 58% and 26% of the 2019 count, although filings keep rising (Appendix B.3). The EU countries have 50% of employment and 42% of GDP, but they receive 11% of VC and produce 14% of patents. Appendix D documents sources and construction.

5.1 Quantitative model

I add one component to the model of Section 3. A larger local market raises the return to innovation, as in Arkolakis, Lee and Peters (2026) and Desmet, Nagy and Rossi-Hansberg (2026). But population is an imperfect proxy for the market a firm can reach: firms in large countries often serve only part of the country, and firms in small countries often sell abroad (Buera et al., 2026). I therefore let the value of a patent depend on L_i^λ, with $0 \leq \lambda \leq 1$:

$$v_{it} = \bar{\omega} L_i^\lambda \left(r_{it}^K\right)^{-\frac{\alpha}{1-\alpha}} + (1 - \eta_{it} - b_i)\frac{v_{it+1}}{R_{it+1}^k}. \tag{32}$$

The case $\lambda = 1$ is equation (11). Appendix A.7 derives (32): a line has $N_i = L_i^{1-\lambda}$ sub-markets, a patent can be enforced in one of them, and the technology reaches the whole line. Output, profits, innovation and the frontier are as in Section 3, so λ affects the equilibrium only through the patent value.

To connect innovation to the data, I follow Arkolakis, Lee and Peters (2026) and assume that patents are proportional to the arrival rate of innovations, $P_{it} \propto \eta_{it}$, with a constant that is common across locations.

[4]The EU countries are Austria, Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, the Netherlands, Poland, Portugal, Spain and Sweden.

5.2 Calibration and estimation

Table 4 lists the parameters in four groups: those set externally, those estimated, those taken from the data, and the location-specific fundamentals recovered by inverting the model.

Table 4: Model parameters

Symbol	Role	Value	Source or target
Panel A: Set externally			
β	Discount factor	0.97	Annual benchmark
g	Gross frontier growth	1.02	2% annual growth
α	Production elasticity	0.43	Implies $\alpha/\mu \simeq 1/3$
μ	Intermediate-goods markup	1.30	
δ_K	Capital depreciation	0.08	
κ	Innovation step size	1.20	Acemoglu et al. (2018); Akcigit and Kerr (2018)
γ	R&D curvature	2.00	Acemoglu et al. (2018)
σ	Elasticity of innovation to VC intensity	0.05	Moretti (2021)
λ	Elasticity of patent value to size	0.15	
ζ	Participation-cost curvature	1.00	Linear marginal cost
ϵ	Portfolio elasticity	10	Kleinman et al. (2023)
Panel B: Disciplined by indirect inference			
ν_b	Sensitivity of adoption to citation home bias	0.05	TFP regression on citation home bias
$\bar{b}$	Mean adoption probability	0.0088	Spread of log GDP per worker at PPP
Panel C: From the data			
L_i	Labor input		Employment data
τ_{in}	Bilateral frictions, $i \neq n$		Estimates from Section 4
b_i	Adoption, relative to $\bar{b}$		Citation home bias, equation (33)
Panel D: Inverted from the model			
χ_i	Innovation efficiency		Share of VC-backed patents
φ_i	Participation cost		VC outflow over GDP

I set the discount factor to $\beta = 0.97$, physical-capital depreciation to $\delta_K = 0.08$, and the gross frontier growth target to $g = 1.02$. I set the intermediate-goods markup to $\mu = 1.30$ and the production elasticity to $\alpha = 0.43$, which imply a physical-capital income share of $\alpha/\mu \simeq 0.33$.

I set the innovation step size to $\kappa = 1.20$, in line with quantitative endogenous growth models (Acemoglu et al., 2018; Akcigit and Kerr, 2018). With the growth target, this pins down the aggregate innovation rate: $\sum_i \eta_i = (g-1)/(\kappa-1) = 0.10$. I set $\gamma = 2$, so that $1/\gamma = 0.5$, the standard value for the elasticity of innovation to R&D (Acemoglu et al., 2018). I set $\sigma = 0.05$, close to the elasticity of inventor patents with respect to

local cluster size of 0.066 in Moretti (2021).

The participation-cost curvature $\zeta = 1$ governs how household VC investment responds to the return premium. With $\zeta = 1$ the marginal participation cost rises linearly with VC over GDP. The portfolio elasticity is $\epsilon = 10$, following Kleinman et al. (2023). The frictions τ_{in} are those estimated in Section 4, with $\tau_{ii} = 1$.

Technology adoption. The model also needs the probability b_i with which each location adopts frontier technologies. I do not observe adoption directly, so I use a simple proxy based on patent citations. Let h_i^c be the odds that location i's patents cite patents from i rather than from another location, relative to the same odds among patents from elsewhere. I assume that locations with lower citation home bias adopt frontier technologies faster:

$$b_i = \bar{b} \exp\left[-\nu_b \left(\log h_i^c - \frac{1}{N}\sum_{j=1}^{N} \log h_j^c\right)\right]. \tag{33}$$

Here $\bar{b}$ is the geometric mean adoption probability and ν_b is the sensitivity to home bias. Patent citations are the standard measure of knowledge flows between locations (Jaffe, Trajtenberg and Henderson, 1993; Jaffe and Trajtenberg, 2002), and they have been used to measure how ideas diffuse across countries (Eaton and Kortum, 1996; Peri, 2005). I set $\nu_b = 0.05$ and $\bar{b} = 0.0088$. The value of ν_b lies inside the confidence interval of an indirect inference estimate (Gouriéroux, Monfort and Renault, 1993; Smith, 1993), which matches a regression of log TFP on $\log h_i^c$ and $\log \eta_i$ across 29 European countries in the data and in the model. The value of $\bar{b}$ matches the standard deviation of log GDP per worker at purchasing power parity across the 62 locations. Most of the calibration of adoption comes from $\bar{b}$, which sets how far locations with few VC-backed patents are from the frontier. Appendix D.3 describes the estimation, and Appendix D.6 shows that the policy results barely change with homogeneous adoption or with $\nu_b = 0.15$.

5.2.1 Fundamentals recovered by model inversion

Innovation efficiency. The innovation technology at destination i is $\eta_i = \chi_i q_i^{1/\gamma}(q_i/y_i)^{\sigma}$, where q_i is VC-financed research expenditure. The parameter χ_i captures differences across locations in human capital, research quality, institutions and technological capabilities.

I choose χ_i so that the model matches each location's share of VC-backed patents, $P_i / \sum_n P_n$. Only patent shares enter, so the constant linking patents to innovation does not need to be estimated. Using $g = 1 + (\kappa - 1)\sum_n \eta_n$,

$$\eta_i = \frac{g-1}{\kappa - 1}\frac{P_i}{\sum_n P_n}, \qquad \chi_i = \frac{\eta_i}{q_i^{1/\gamma}(q_i/y_i)^{\sigma}}. \tag{34}$$

Once η_i is set, the rest of the equilibrium does not depend on χ_i. I therefore solve for q_i first and then obtain χ_i from (34).

Household VC participation. I choose φ_i so that VC invested by each location, relative to its GDP, matches the data:

$$\frac{g s_i^v}{y_i} = \frac{O_i}{Y_i^{\text{data}}} \equiv o_i,$$

where O_i is VC invested by origin i within the sample and Y_i^{data} is observed GDP, both in current US dollars. The participation condition (23), with $R^k = g/\beta$, then gives

$$\varphi_i = \frac{\beta R_i^v / g - 1}{o_i^\zeta}. \tag{35}$$

5.3 Model fit

Patent shares and each location's VC outflow over GDP are matched by construction, and the spread of log output per worker at purchasing power parity is matched by $\bar{b}$. VC inflow shares and domestic shares are partly targeted, since the frictions are estimated on the same flows. The log correlation of inflow shares with the data is 0.95, and the correlation of domestic shares is 0.83.

The spread of output per worker is targeted, but its pattern across locations is not. Model output per worker has a log correlation of 0.36 with GDP per worker at purchasing power parity across the 62 locations, 0.59 within the EU and 0.38 within the US. The root mean squared log discrepancy is 0.19. The technology index a_i has a log correlation of 0.59 with Penn World Table TFP across the 17 European countries of the model. This comparison is partly targeted, since ν_b is set with a TFP regression.

I compare the EU and the US by total output over total employment in each bloc. In the model, EU output per worker is 86% of the US level, a log gap of -0.15. In the data, at purchasing power parity, it is 73%, a gap of -0.32. The model does better on TFP. I compare $a_i^{1-\alpha}$ with Penn World Table TFP, both averaged with employment weights: the EU–US gap is -0.07 in the model, against -0.06 in the data over 2000–2019 and -0.12 over 2010–2019. Appendix D.5 shows the fit charts and metrics.

5.4 Recovered fundamentals

Figure 4 shows the two inverted fundamentals. Innovation efficiency χ_i is highest in California, followed by Massachusetts, the UK, Germany, France and Texas. It has a log correlation of 0.68 with business R&D/GDP across 61 locations, which the inversion does not target. I do not expect the two to match. In the model, research is financed by VC, which I use as a proxy for the resources that startups receive over the years. Business

R&D instead covers the research of all firms in the economy, including large incumbents that do not rely on VC. Innovation efficiency is not the same as productivity a_i, which also depends on how much a location innovates and how fast it adopts the frontier.

The participation cost φ_i reconciles VC supply with the equilibrium return premium. Within the EU it is lowest in Estonia, Denmark and Sweden. It is also related to how households save, which the inversion does not target. Across the 16 EU countries, $\log \varphi_i$ has a correlation of -0.66 with log funded pension assets over GDP. Across the 45 US states, it has a correlation of -0.47 with the log share of market assets in household portfolios. Across EU countries the correlation with the household share is weak, at -0.06, so the link in Europe runs through funded pensions rather than direct household holdings. Both fundamentals also absorb anything the model omits, so I read them as related to how savings are organized, not as direct measures of regulation.

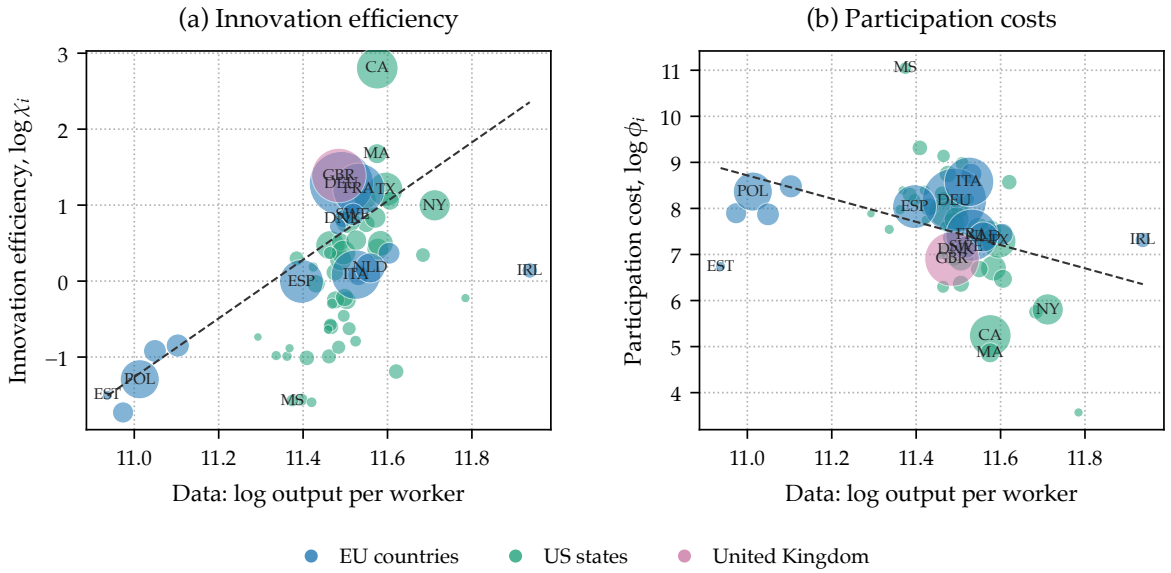


Figure 4: Recovered fundamentals and output per worker.

Notes: Each circle is a location, and its size is proportional to employment. Innovation efficiency is relative to its geometric mean. The horizontal axis is log output per worker in the data, at purchasing power parity. The dashed line is an employment-weighted least-squares fit. Its slope is 3.86 (s.e. 0.63) for $\log \chi_i$ and -2.52 (s.e. 0.71) for $\log \varphi_i$, and both are significant at the 1% level.

6 Gains from Integration

This section uses the model to ask how much of the productivity gap between the EU and the US closes when investing across EU borders becomes cheaper and when EU households can invest more easily in VC. I then compare these policies with closing the differences in innovation efficiency and adoption between the two blocs.

6.1 Policy experiments

I run four experiments. The first removes home bias on investment between EU countries by setting $h_i = 1$ in (25) for these pairs. The border still applies when EU investors invest in the UK or the US. This lowers the median τ_{in} between EU countries from 1.68 to 1.07. The second experiment sets the participation cost φ_i of every EU country to the lowest value in the EU, which is Estonia's. Since φ_i is lower in countries with larger funded pension assets (Section 5.4), I read this experiment as a reform that makes it easier for households to invest in market-based savings, for example through funded pensions. The third sets the distance elasticity between EU countries equal to the one between US states, which lowers it in absolute value from 0.41 to 0.14. The fourth combines the three changes.

In every experiment innovation efficiency χ_n, adoption b_n, employment and all parameters stay at their baseline values, and I compare balanced growth paths before and after the change. To measure the productivity gap, I divide total output by total employment in each bloc and take the log difference between the EU and the US. In the baseline the gap is -0.15, which means that output per worker in the EU is 86% of the US level.

6.2 Results

Table 5: Effects of the experiments

	Δg	EU investors' VC going to (%)				EU VC / GDP (%)		EU innov. share	EU a (% of	Gap closed
	(pp)	Own	Other EU	US	UK	Invested	Received	(%)	US)	(%)
Baseline	–	71	18	8	4	0.032	0.066	14.1	86.4	–
(1) Home bias	0.026	13	84	2	1	0.045	0.067	14.8	86.9	3.8
(2) Particip. costs	0.050	60	18	16	6	0.076	0.081	15.0	87.2	6.4
(3) Distance	0.001	67	22	7	4	0.033	0.066	14.1	86.4	0.1
(4) Combined	0.110	8	79	9	4	0.103	0.094	17.4	88.9	19.1

Notes: EU is the 16 EU countries in the model. VC shares are within the 62 model locations. VC invested over GDP and the share of innovation are targeted in the baseline, and the VC shares and VC received are not. "EU a" is total EU output per worker as a percentage of the US level. "Gap closed" is the share of the baseline log gap (-0.15) that the experiment closes. "Combined" applies experiments (1) to (3) together.

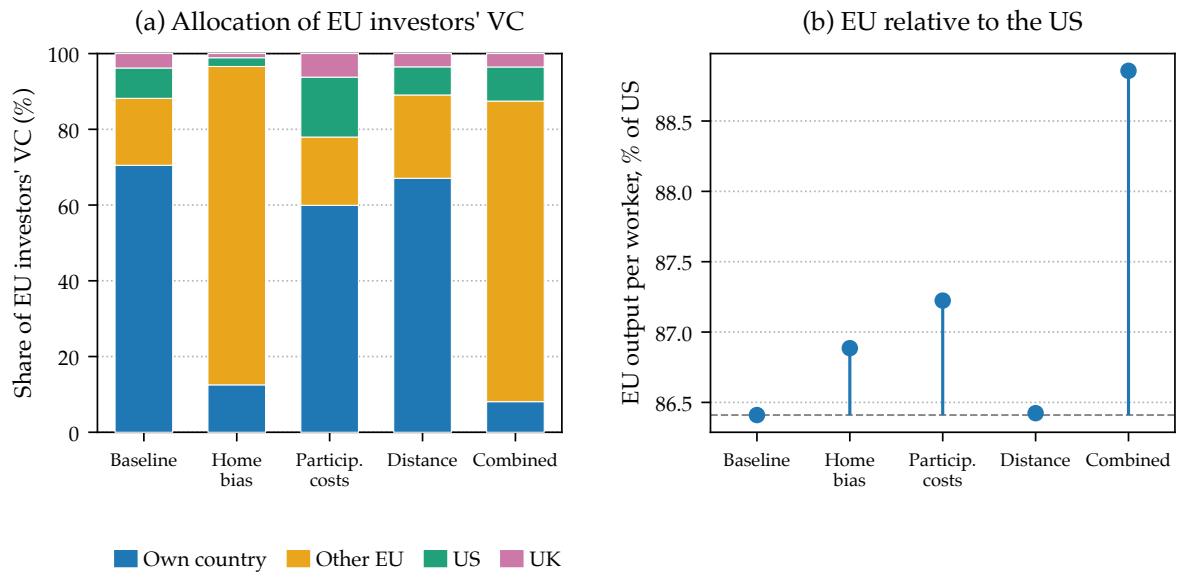


Figure 5: Allocation of VC and the productivity gap in each experiment.
Notes: Panel (a) shows where EU investors place their VC, within the 62 model locations. Panel (b) shows total EU output per worker as a percentage of the US level. The dashed line is the baseline.

Table 5 and Figure 5 show the results. The two policies work through different margins. Lowering participation costs mainly increases how much EU households invest in VC, with a smaller effect on where the money goes. Removing home bias mainly changes where it goes.

Consider participation costs first. When the cost falls, households invest more in VC, and intermediaries divide this money across destinations according to returns and frictions. VC invested by EU investors more than doubles, and their portfolio shifts towards the US. The share they invest in the US rises from 8% to 16%, and the share they keep in the EU falls from 89% to 78%. Part of the new money goes to the US, and much of the rest replaces foreign investors in EU startups, because EU returns fall as more EU money arrives. As a result, VC received by EU startups rises by only 23%. EU output per worker rises by 0.9% relative to the US, which closes 6.4% of the gap.

Removing home bias instead changes where EU money goes. EU investors now place 84% of their VC in other EU countries, against 18% in the baseline. They also invest more, 0.045% of GDP against 0.032%, because lower barriers raise the return on VC. VC received by EU startups barely changes, because EU money replaces investment from the US and the UK. However, R&D rises, because less of each dollar is lost to frictions. EU output per worker rises by 0.6% relative to the US, which closes 3.8% of the gap. Giving EU countries the barriers of US states would close almost nothing, because investors in US states are also home-biased.

A lower distance elasticity on its own does almost nothing. EU investors move some VC from home to other EU countries, whose share rises from 18% to 22%, but only 0.1%

of the gap closes.

When the three changes are combined, EU output per worker rises by 2.8% relative to the US and 19.1% of the gap closes, almost twice the sum of the three separate effects, 10.3%. The distance change is not behind this. Without it, the two policies together close 17.7% of the gap, against 10.2% for the sum of their separate effects. The policies complement each other: lower participation costs increase the amount of EU money, and lower barriers send more of it to other EU countries, where each dollar produces more R&D. EU investors place 87% of their VC in the EU under the combined policy, against 78% when only participation costs fall. This suggests that the two policies need to be coordinated, since participation costs depend on national policies, while barriers between EU countries depend on EU-level ones.

The growth rate rises from 2.00% to 2.11%. However, the gap narrows only because US productivity falls relative to the frontier. Since a_n measures productivity relative to the frontier, faster frontier growth lowers it in the US, where innovation rises less. EU productivity relative to the frontier falls slightly. Productivity grows faster everywhere on the new balanced growth path, so the main gain from the reforms is faster growth for everyone, with a modest narrowing of the gap.

6.3 The distribution within the EU

The two policies also have different effects within the EU. Lower participation costs help most the countries where costs were highest, and they make the supply of VC more concentrated in Germany and France. Removing home bias spreads the supply of VC more widely. However, VC received falls in Poland, Hungary and Portugal, whose startups lose the advantage they had with their own investors.

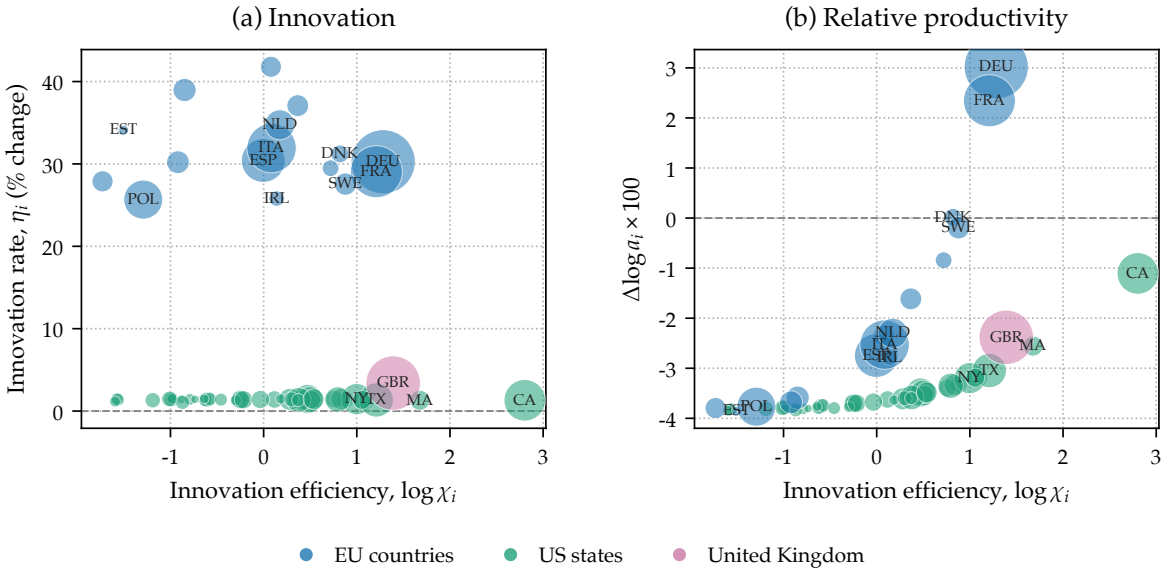


Figure 6: Experiment (4) by location, against innovation efficiency χ_n. Circle size is proportional to employment.

Figure 6 shows the changes by location under the combined policy. Innovation rises by between 26% and 42% in every EU country. However, relative productivity rises only in Germany, France and Denmark, the EU countries with the highest innovation efficiency. Where χ_n is low, adoption matters more than own innovation, so even a large increase in innovation does not keep up with the faster frontier. As a result, productivity becomes more unequal across EU countries: the employment-weighted standard deviation of log a_n rises from 0.15 to 0.18.

6.4 How much do efficiency and adoption matter?

The policies leave innovation efficiency and adoption unchanged, although both differ between the EU and the US. The employment-weighted mean of log χ_n is 0.28 lower in the EU than in the US, and the mean of log b_n is 0.03 lower. To see how much these differences matter, I raise every EU country by the same factor until the EU mean equals the US mean. Table 6 reports the results.

Table 6: Bringing EU efficiency and adoption to the US level

	Δg	EU investors' VC going to (%)				EU VC / GDP (%)		EU innov. share	EU a (% of	Gap closed
	(pp)	Own	Other EU	US	UK	Invested	Received	(%)	US)	(%)
Efficiency χ	0.113	74	19	5	2	0.038	0.094	21.4	92.2	44.6
Adoption b	-0.000	70	18	8	4	0.032	0.065	14.0	88.0	12.2
Both	0.113	74	19	5	2	0.038	0.092	21.3	93.7	55.5
Both and policy (4)	0.263	9	84	5	2	0.121	0.123	25.1	96.8	77.6

Notes: Same baseline and definitions as Table 5. Means are employment-weighted log means. Every EU country is raised by the same factor until the EU mean equals the US mean. The UK and the US keep their baseline χ_n and b_n.

Raising the EU means closes much more of the gap than the policies. Higher efficiency closes 45% of the gap and higher adoption 12%, and together they close 56%. Adoption matters less because, at $\nu_b = 0.05$, citation home bias does little to distinguish fast and slow adopters, so the adoption gap between the EU and the US is small. In the model, differences in innovation efficiency therefore matter more for the EU–US gap than differences in adoption or the financial barriers I remove.

6.5 Robustness

Finally, I check whether the results depend on how adoption is calibrated. With homogeneous adoption, or with $\nu_b = 0.15$, which is above the point estimate of 0.116, the combined policy raises EU output per worker relative to the US by between 2.5% and 3.0%. With GDP at market exchange rates, 64 locations and $\nu_b = 0.15$, the effect rises to 4.0%, because adoption is slower and innovation matters more for productivity. The share of the gap closed falls to 14.3%, because the model gap is larger, at -0.27 (Appendix D.6). Adding a destination payoff that makes the model match the VC received by each location raises the effect of removing home bias from 3.8% to 7.6% of the gap, and the combined policy then closes 22.8% (Appendix D.7).

7 Conclusion

This paper studies how capital market frictions shape innovation-led growth in a multi-country setting. Empirically, I document a large integration gap between venture capital allocation across US states and across EU countries, with VC in Europe more home-biased and more sensitive to distance.

To interpret these facts, I develop a multi-country endogenous growth model in which competitive intermediaries allocate household savings to R&D projects across locations, subject to bilateral investment frictions and idiosyncratic return shocks. Households

choose to save in a low-risk asset or through VC, subject to participation costs. Participation costs determine how much funding intermediaries receive, while cross-border barriers govern where this funding goes.

I quantify the model with bilateral VC flows and the patents of VC-backed firms, and run four experiments in the EU. Lowering participation costs raises the amount of VC that EU investors supply, but it changes their portfolios much less, so part of the new money goes to the US and much of the rest replaces foreign investors. Removing home bias within the EU reallocates EU money towards other EU countries and lets each dollar buy more R&D. Lower participation costs raise EU output per worker relative to the US by 0.9%, and removing home bias by 0.6%. Together, and with a distance elasticity between EU countries equal to the one between US states, they raise it by 2.8% and close 19% of the EU–US productivity gap in the model, more than the sum of the two, which points to coordination between national policies on participation and EU-level policies on barriers. All of the fall in the gap comes from lower relative productivity in the US, as the frontier grows faster, and EU productivity relative to the frontier falls slightly. Productivity still grows faster everywhere on the new path, so the main gain is faster growth, with a modest narrowing of the gap. The combined policy also makes innovation less concentrated across locations, but relative productivity rises only in the three EU countries with the highest innovation efficiency. The two policies also have different effects within the EU. Lower participation costs concentrate VC supply further in Germany and France, while removing home bias spreads supply more widely and lowers the VC received in Poland, Hungary and Portugal.

Finally, raising the EU means of innovation efficiency and adoption to the US means closes more than half of the gap in the model, most of it through efficiency. Financial integration and participation reforms therefore matter, but they are not enough on their own: the productivity of research accounts for a larger part of the gap. EU passports act on how funds raise money from their investors, while the frictions I estimate act on how funds invest in start-ups across borders. Linking these frictions to specific reforms, such as the *EU Inc.* regime, is a natural next step, together with studying the transition and its welfare consequences, since I compare balanced growth paths.

References

Acemoglu, D., Akcigit, U., Alp, H., Bloom, N., and Kerr, W. (2018). Innovation, reallocation, and growth. *American Economic Review*, 108(11):3450–91.

Acemoglu, D. and Cao, D. (2015). Innovation by entrants and incumbents. *Journal of Economic Theory*, 157:255–294.

Aghion, P. and Howitt, P. (2005). Growth with quality-improving innovations: an integrated framework. *Handbook of economic growth*, 1:67–110.

Aghion, P., Howitt, P., and Mayer-Foulkes, D. (2004). The effect of financial development on convergence: Theory and evidence. Working Paper 10358, National Bureau of Economic Research.

Aghion, P., Howitt, P., and Mayer-Foulkes, D. (2005). The effect of financial development on convergence: Theory and evidence. *The quarterly journal of economics*, 120(1):173–222.

Akcigit, U., Ates, S. T., Lerner, J., Townsend, R. R., and Zhestkova, Y. (2024). Fencing off Silicon Valley: Cross-border venture capital and technology spillovers. *Journal of Monetary Economics*, 141:14–39.

Akcigit, U., Dinlersoz, E., Greenwood, J., and Penciakova, V. (2022). Synergizing ventures. *Journal of Economic Dynamics and Control*, 143:104427.

Akcigit, U. and Kerr, W. R. (2018). Growth through heterogeneous innovations. *Journal of Political Economy*, 126(4):1374–1443.

Anderson, J. E. and van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. *American Economic Review*, 93(1):170–192.

Arkolakis, C., Lee, S. K., and Peters, M. (2026). Immigration, innovation, and the geography of growth. NBER Working Paper 35392, National Bureau of Economic Research.

Arnold, N., Claveres, G., and Frie, J. (2024). Stepping up venture capital to finance innovation in Europe. Technical Report 24/146, International Monetary Fund (IMF).

Asdrubali, P. (2023). Patterns of Cross-Border Venture Capital Flows in Europe. European Economy - Discussion Papers 195, Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

Beck, R., Coppola, A., Lewis, A. J., Maggiori, M., Schmitz, M., and Schreger, J. (2024). The geography of capital allocation in the Euro area. Working Paper 32275, National Bureau of Economic Research.

Benigno, G. and Fornaro, L. (2018). Stagnation traps. *The Review of Economic Studies*, 85(3):1425–1470.

Benigno, G., Fornaro, L., and Wolf, M. (2025). The global financial resource curse. *American Economic Review*, 115(1):220–262.

Bergeaud, A., Guillouzouic, A., Henry, E., and Malgouyres, C. (2022). From public labs to private firms: magnitude and channels of R&D spillovers. CEP Discussion Paper 1882, Centre for Economic Performance, London School of Economics.

Bergeaud, A. and Verluise, C. (2022). The rise of China's technological power: the perspective from frontier technologies. CEP Discussion Paper 1876, Centre for Economic Performance, London School of Economics.

Berger, M., Calligaris, S., Dechezleprêtre, A., Dernis, H., Greppi, A., Kirpichev, D., and Muñoz Alvarado, A. (2026). The OECD start-ups database: A new lens on the global entrepreneurial ecosystems. OECD Science, Technology and Industry Working Papers 2026/04, OECD Publishing.

Berkes, E., Manysheva, K., and Mestieri, M. (2022). Global innovation spillovers and productivity: Evidence from 100 years of world patent data. CEPR Discussion Paper DP17285, Centre for Economic Policy Research.

Bernstein, S., Giroud, X., and Townsend, R. R. (2016). The impact of venture capital monitoring. *The Journal of Finance*, 71(4):1591–1622.

Broner, F. and Ventura, J. (2016). Rethinking the effects of financial globalization. *The quarterly journal of economics*, 131(3):1497–1542.

Buera, F. J., Kornejew, M., Ma, Y., Oberfield, E., and Trachter, N. (2026). Innovation and development over the (very) long run. Working paper.

Buera, F. J. and Oberfield, E. (2020). The global diffusion of ideas. *Econometrica*, 88(1):83–114.

Cai, J., Li, N., and Santacreu, A. M. (2022). Knowledge diffusion, trade, and innovation across countries and sectors. *American Economic Journal: Macroeconomics*, 14(1):104–145.

Capelle, D. and Pellegrino, B. (2025). Unbalanced financial globalization. Working Paper 34121, National Bureau of Economic Research.

Carlino, G. and Kerr, W. R. (2015). Agglomeration and innovation. In Duranton, G., Henderson, J. V., and Strange, W. C., editors, *Handbook of Regional and Urban Economics*, volume 5, pages 349–404. Elsevier.

Chatterji, A., Glaeser, E., and Kerr, W. (2014). Clusters of entrepreneurship and innovation. *Innovation policy and the economy*, 14(1):129–166.

Chen, H., Gompers, P., Kovner, A., and Lerner, J. (2010). Buy local? the geography of venture capital. *Journal of Urban Economics*, 67:90–102.

Chen, J. and Ewens, M. (2025). Venture capital and startup agglomeration. *The Journal of Finance*, 80(4):2153–2198.

Coe, D. T. and Helpman, E. (1995). International r&d spillovers. *European economic review*, 39(5):859–887.

Cole, H. L., Greenwood, J., and Sanchez, J. M. (2016). Why doesn't technology flow from rich to poor countries? *Econometrica*, 84(4):1477–1521.

Comin, D. and Hobijn, B. (2010). An exploration of technology diffusion. *American Economic Review*, 100(5):2031–2059.

Desmet, K., Nagy, D. K., and Rossi-Hansberg, E. (2018). The geography of development. *Journal of Political Economy*, 126(3):903–983.

Desmet, K., Nagy, D. K., and Rossi-Hansberg, E. (2026). Human capital accumulation across space. Working paper.

D'Amico, L. and Alekseev, M. (2025). Capital market integration and growth across the United States. Working paper, Joint Center for Housing Studies, Harvard University.

Eaton, J. and Kortum, S. (1996). Trade in ideas patenting and productivity in the OECD. *Journal of international Economics*, 40(3-4):251–278.

Eaton, J. and Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, 70(5):1741–1779.

ECB (2024). Financial integration and structure in the Euro area. Technical report, ECB Committee on Financial Integration.

EIB (2024a). European Investment Bank VC survey 2024 – market sentiment. Technical Report 2024/99, EIF Market Assessment & Research.

EIB (2024b). The scale-up gap: Financial market constraints holding back innovative firms in the European Union. Technical report, European Investment Bank.

Eichengreen, B. and Saka, O. (2025). Cultural stereotypes of multinational banks. *Journal of the European Economic Association*.

Ewens, M. and Farre-Mensa, J. (2020). The deregulation of the private equity markets and the decline in IPOs. *The Review of Financial Studies*, 33(12):5463–5509.

Ewens, M. and Farre-Mensa, J. (2022). Private or public equity? the evolving entrepreneurial finance landscape. *Annual Review of Financial Economics*, 14(1):271–293.

Feenstra, R. C., Inklaar, R., and Timmer, M. P. (2015). The next generation of the Penn World Table. *American Economic Review*, 105(10):3150–3182.

Gompers, P. A. and Lerner, J. (1998). What drives venture capital fundraising? *Brookings Papers on Economic Activity. Microeconomics*, pages 149–204.

Gouriéroux, C., Monfort, A., and Renault, E. (1993). Indirect inference. *Journal of Applied Econometrics*, 8(S1):S85–S118.

Greenwood, J., Han, P., and Sanchez, J. M. (2022). Financing ventures. *International Economic Review*, 63(3):1021–1053.

Grossman, G. M. and Helpman, E. (1991). Quality ladders in the theory of growth. *The Review of Economic Studies*, 58(1):43–61.

Hall, B. H., Jaffe, A., and Trajtenberg, M. (2005). Market value and patent citations. *RAND Journal of Economics*, 36(1):16–38.

Head, K. and Mayer, T. (2014). Gravity equations: Workhorse, toolkit, and cookbook. In *Handbook of international economics*, volume 4, pages 131–195. Elsevier.

Hochberg, Y. V. and Rauh, J. D. (2013). Local overweighting and underperformance: Evidence from limited partner private equity investments. *The Review of Financial Studies*, 26(2):403–451.

Howitt, P. (2000). Endogenous growth and cross-country income differences. *American Economic Review*, 90(4):829–846.

Jaffe, A. B. and Trajtenberg, M. (2002). *Patents, citations, and innovations: A window on the knowledge economy*. MIT press.

Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *the Quarterly journal of Economics*, 108(3):577–598.

Jovanovic, B. and Szentes, B. (2013). On the market for venture capital. *Journal of Political Economy*, 121(3):493–527.

Kaplan, S. N. and Stromberg, P. (2001). Venture capitalists as principals: Contracting, screening, and monitoring. *American Economic Review*, 91(2):426–430.

Karlsen, J., Kisseleva, K., Mjøs, A., and Robinson, D. T. (2024). Are some angels better than others? Working Paper 33231, National Bureau of Economic Research.

Keller, W. (2002). Geographic localization of international technology diffusion. *American Economic Review*, 92(1):120–142.

Kerr, W. R. and Robert-Nicoud, F. (2020). Tech clusters. *Journal of Economic Perspectives*, 34(3):50–76.

Keuschnigg, C. (2004). Venture capital backed growth. *Journal of Economic Growth*, 9(2):239–261.

Kleinman, B., Liu, E., and Redding, S. J. (2023). Dynamic spatial general equilibrium. *Econometrica*, 91(2):385–424.

Kleinman, B., Liu, E., Redding, S. J., and Yogo, M. (2023). Neoclassical growth in an interdependent world. Working Paper 31951, National Bureau of Economic Research.

Kortum, S. and Lerner, J. (2000). Assessing the contribution of venture capital to innovation. *The RAND Journal of Economics*, 31(4):674–692.

La Porta, R., Lopez-de Silanes, F., and Shleifer, A. (2008). The economic consequences of legal origins. *Journal of Economic Literature*, 46(2):285–332.

Lagarde, C. (2024). Follow the money: channelling savings into investment and innovation in Europe. Speech at the 34th European Banking Congress: "Out of the Comfort Zone: Europe and the New World Order". Delivered on 22 November 2024.

Lerner, J., Liu, J., Moscona, J., and Yang, D. Y. (2024). Appropriate entrepreneurship? the rise of China and the developing world. Working Paper 32193, National Bureau of Economic Research.

Lerner, J. and Nanda, R. (2020). Venture capital's role in financing innovation: What we know and how much we still need to learn. *Journal of Economic Perspectives*, 34(3):237–61.

Liu, E. and Ma, S. (2021). Innovation networks and R&D allocation. Working Paper 29607, National Bureau of Economic Research.

Martin, P. and Rey, H. (2004). Financial super-markets: Size matters for asset trade. *Journal of International Economics*, 64(2):335–361.

Matsuyama, K. (2004). Financial market globalization, symmetry-breaking, and endogenous inequality of nations. *Econometrica*, 72(3):853–884.

Mayer, T. and Zignago, S. (2011). Notes on CEPII's distances measures: The GeoDist database. Working Paper 2011-25, CEPII.

Moretti, E. (2021). The effect of high-tech clusters on the productivity of top inventors. *American Economic Review*, 111(10):3328–3375.

Novy, D. (2013). Gravity redux: Measuring international trade costs with panel data. *Economic Inquiry*, 51(1):101–121.

Opp, C. C. (2019). Venture capital and the macroeconomy. *The Review of Financial Studies*, 32(11):4387–4446.

Pellegrino, B., Spolaore, E., and Wacziarg, R. (2025). Barriers to global capital allocation. *The Quarterly Journal of Economics*, 140(4):3067–3131.

Peri, G. (2005). Determinants of knowledge flows and their effect on innovation. *Review of Economics and Statistics*, 87(2):308–322.

Rosenthal, S. S. and Strange, W. C. (2001). The determinants of agglomeration. *Journal of Urban Economics*, 50(2):191–229.

Saxenian, A. (1996). *Regional Advantage: Culture and Competition in Silicon Valley and Route 128*. Harvard University Press.

Silva, J. M. C. S. and Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics*, 88(4):641–658.

Smith, A. A. (1993). Estimating nonlinear time-series models using simulated vector autoregressions. *Journal of Applied Econometrics*, 8(S1):S63–S84.

Thompson, P. and Fox-Kean, M. (2005). Patent citations and the geography of knowledge spillovers: A reassessment. *American Economic Review*, 95(1):450–460.

Tian, X. (2011). The causes and consequences of venture capital stage financing. *Journal of Financial Economics*, 101(1):132–159.

Trouvain, F. (2026). Technology adoption, innovation, and inequality in a global world. Working paper, University of Oxford.

A Theory Appendix

I derive the equilibrium conditions and the balanced growth path of the model in Section 3 below. Appendix A.7 derives the market-size term used in Section 5.1, and Appendix A.8 gives more detail on the assumptions in Section 3.6.

A.1 Final goods, intermediates and profits

Let P_{it}^j denote the price of intermediate j in country i. The final-good producer takes prices as given, and its first-order conditions are

$$W_{it} = (1-\alpha)L_i^{-\alpha}\int_0^1 \left(A_{it}^j\right)^{1-\alpha}\left(x_{it}^j\right)^{\alpha} dj,$$
$$P_{it}^j = \alpha L_i^{1-\alpha}\left(A_{it}^j\right)^{1-\alpha}\left(x_{it}^j\right)^{\alpha-1}.$$

The patent holder produces one unit of x_{it}^j with one unit of capital, at marginal cost r_{it}^K. Facing the inverse demand above, an unconstrained monopolist would charge r_{it}^K/α. The competitive fringe produces at cost μr_{it}^K, so when $\mu < 1/\alpha$ the patent holder sets the limit price $P_{it}^j = \mu r_{it}^K$. Inverting the demand curve at this price gives (5), and line profits are

$$\pi_{it}^j = (\mu-1)r_{it}^K x_{it}^j = \bar{\omega} A_{it}^j L_i \left(r_{it}^K\right)^{-\frac{\alpha}{1-\alpha}}, \qquad \bar{\omega} \equiv (\mu-1)\left(\frac{\alpha}{\mu}\right)^{\frac{1}{1-\alpha}}.$$

Because x_{it}^j is proportional to A_{it}^j, aggregation is exact. Integrating over lines with $A_{it} = \int_0^1 A_{it}^j dj$ and $K_{it} = \int_0^1 x_{it}^j dj$,

$$r_{it}^K = \frac{\alpha}{\mu}\left(\frac{A_{it}L_i}{K_{it}}\right)^{1-\alpha}, \qquad Y_{it} = (A_{it}L_i)^{1-\alpha}K_{it}^{\alpha},$$
$$r_{it}^K K_{it} = \frac{\alpha}{\mu}Y_{it}, \qquad \Pi_{it} \equiv \int_0^1 \pi_{it}^j dj = \frac{\alpha(\mu-1)}{\mu}Y_{it},$$

which includes (6), and $W_{it}L_i = (1-\alpha)Y_{it}$. Wages, capital rents and monopoly profits exhaust output, since $(1-\alpha) + \alpha/\mu + \alpha(\mu-1)/\mu = 1$.

A.2 Productivity, the frontier and the value of a patent

World frontier. Consider product line j in period t. I abstract from simultaneous successes in the same line, so under the short-period assumption at most one country innovates in it, so the line is improved with probability $\sum_n \eta_{nt}$, which requires $\sum_n \eta_{nt} \leq 1$. A successful innovation sets the innovator's productivity to $\kappa \bar{A}_t^j$, which exceeds every country's current productivity in the line and therefore becomes the new line frontier.

Adoption sets productivity to $\bar{A}_t^j$ and does not move the frontier. Hence

$$\bar{A}_{t+1}^j = \begin{cases} \kappa \bar{A}_t^j & \text{with probability } \sum_n \eta_{nt}, \\ \bar{A}_t^j & \text{with probability } 1 - \sum_n \eta_{nt}. \end{cases}$$

In the symmetric equilibrium the innovation rates do not depend on j, so which lines are improved is independent of their current frontier. With a continuum of lines, integrating gives

$$\bar{A}_{t+1} = \int_0^1 \bar{A}_{t+1}^j dj = \Big[1 + (\kappa - 1) \sum_n \eta_{nt}\Big] \bar{A}_t,$$

which is (9). The short-period assumption follows Benigno and Fornaro (2018), who assume that the probability of two or more projects in the same country and product line succeeding is negligible, and interpret η_{it}^j as the probability that the incumbent is replaced. I assume that the probability of multiple frontier-updating innovations in the same line within a period is negligible, so the replacement event is unique.

Country productivity and the gap. Taking the expectation of (2) in line j, with $\eta_{it}^j = \eta_{it}$ and b_i common across lines, and integrating over lines gives

$$\int_0^1 A_{it+1}^j dj = \eta_{it}\kappa \int_0^1 \bar{A}_t^j dj + b_i \int_0^1 \bar{A}_t^j dj + (1 - \eta_{it} - b_i) \int_0^1 A_{it}^j dj,$$

which is (8). With a continuum of lines, the realized average equals this expectation. Dividing by $\bar{A}_{t+1} = g_{t+1}\bar{A}_t$, relative productivity $a_{it} \equiv A_{it}/\bar{A}_t$ evolves according to

$$a_{it+1} = \frac{\eta_{it}\kappa + b_i}{g_{t+1}} + \frac{1 - \eta_{it} - b_i}{g_{t+1}} a_{it}.$$

With constant η_i and g this map is linear in a_{it}, with slope $c_i \equiv (1 - \eta_i - b_i)/g$. Since $\eta_i + b_i \leq 1$ and $g \geq 1$, $c_i \geq 0$, and $c_i < 1$ whenever $\eta_i + b_i > 0$ or $g > 1$. The map is then a contraction, so it has a unique steady state, $a_i = (\eta_i\kappa + b_i)/(g - 1 + \eta_i + b_i)$, as in (19), and a_{it} converges to it monotonically from any initial value. The steady state is positive whenever $\eta_i + b_i > 0$. It satisfies $a_i \leq 1$ because $g - 1 = (\kappa - 1)\sum_n \eta_n \geq (\kappa - 1)\eta_i$, with equality only if i is the only innovator.

Value of a patent. An incumbent with productivity A_{it}^j earns π_{it}^j and keeps the line next period with probability $1 - \eta_{it} - b_i$. Guess $V_t(A_{it}^j) = v_{it}A_{it}^j$. Substituting the guess and $\pi_{it}^j = \bar{\omega}L_i(r_{it}^K)^{-\alpha/(1-\alpha)}A_{it}^j$ into (10), both sides are linear in A_{it}^j, which verifies the guess with slope (11). With constant r^K, η_i and $R^k = g/\beta$, the bounded solution is

$$v_i = \frac{\bar{\omega}L_i \left(r^K\right)^{-\frac{\alpha}{1-\alpha}}}{1 - (1 - \eta_i - b_i)\beta/g},$$

which is positive if and only if $g/\beta > 1 - \eta_i - b_i$. A successful entrant starts at $\kappa \bar{A}_t^j$, so the expected value of a new patent is $\int_0^1 V_{t+1}(\kappa \bar{A}_t^j) dj = \kappa v_{it+1} \bar{A}_t$, independent of the country's own productivity.

Return to R&D. An entrepreneur in line j of country i takes ρ_{it+1}, v_{it+1} and the externality as given, and chooses research to maximize

$$\eta_{it}^j \, \kappa v_{it+1} \bar{A}_t^j - \rho_{it+1} Q_{it}^j.$$

Using (1), the first-order condition is

$$\rho_{it+1} = \frac{1}{\gamma} \frac{\eta_{it}^j}{Q_{it}^j} \kappa v_{it+1} \bar{A}_t^j.$$

Since η_{it}^j depends on Q_{it}^j only through $Q_{it}^j / \bar{A}_t^j$, this condition gives the same ratio $Q_{it}^j / \bar{A}_t^j$ in every line. Hence $Q_{it}^j / \bar{A}_t^j = Q_{it} / \bar{A}_t$, and the innovation rate is common across lines:

$$\eta_{it} = \chi_i \left(\frac{Q_{it}}{\bar{A}_t} \right)^{\frac{1}{\gamma}} \left(\frac{Q_{it-1}}{Y_{it-1}} \right)^{\sigma}. \tag{A.1}$$

Substituting into the first-order condition gives (12).

A.3 Fréchet allocation and structural gravity

Each intermediary l in origin i invests the same amount S_{it+1}^v, since intermediaries have measure one. Its payoff per unit invested in destination n is $u_{in}(l) = \phi_{in}(l) \rho_n / \tau_{in}$, where time subscripts are dropped. Because $\phi_{in}(l)$ is Fréchet with shape ϵ and unit scale, u_{in} is Fréchet with scale $\Phi_{in} \equiv (\rho_n / \tau_{in})^{\epsilon}$:

$$\Pr\left[u_{in} \leq x\right] = \exp\left(-\Phi_{in} x^{-\epsilon}\right).$$

Let $\Phi_i \equiv \sum_m \Phi_{im}$.

Allocation. Destination n is chosen when it offers the highest payoff:

$$z_{in} = \int_0^{\infty} \prod_{m \neq n} e^{-\Phi_{im} x^{-\epsilon}} \, d\left(e^{-\Phi_{in} x^{-\epsilon}}\right) = \frac{\Phi_{in}}{\Phi_i} = \frac{(\rho_n / \tau_{in})^{\epsilon}}{\sum_m (\rho_m / \tau_{im})^{\epsilon}},$$

which is (13).

Expected return. The maximum payoff $\max_m u_{im}$ is Fréchet with scale Φ_i, so for $\epsilon > 1$ its mean is

$$\nu_i = \Gamma\left(1 - \frac{1}{\epsilon}\right)\Phi_i^{1/\epsilon},$$

which is (14). A standard property of the Fréchet distribution is that the distribution of the maximum, conditional on destination n being chosen, does not depend on n. Hence the expected payoff is ν_i in every destination.

Zero profit. Destination n receives the financial flow $\widetilde{Q}_{in} = z_{in}S_i^v$ from origin i. Its effective R&D is $Q_n = \sum_i S_i^v \int_{l\to n} \phi_{in}(l)/\tau_{in}\, dl$, where the integral is over the intermediaries that choose n. Multiplying by ρ_n turns each term into realized payoffs:

$$\rho_n Q_n = \sum_i S_i^v \int_{l\to n} u_{in}(l)\, dl = \sum_i S_i^v\, z_{in}\, \mathbb{E}\left[u_{in} \mid n \text{ chosen}\right] = \sum_i z_{in} S_i^v \nu_i,$$

which is (17).

Gravity. Substituting the allocation into $\widetilde{Q}_{in} = z_{in}S_i^v$ gives (24). Origin fixed effects absorb VC supply and multilateral resistance Φ_i, and destination fixed effects absorb $\epsilon \log \rho_n$. Bilateral covariates therefore identify $\epsilon \log \tau_{in}$, up to the normalization $\tau_{ii} = 1$.

A.4 Equilibrium conditions

A competitive equilibrium is a sequence of the variables

$$\{C_{it}, S_{it+1}^v, K_{it+1}, R_{it}^k, R_{it}^v, r_{it}^K, W_{it}, Y_{it}, D_{it}, Q_{it}, \eta_{it}, A_{it}, \bar{A}_t, v_{it}, \rho_{it}, \nu_{it}, z_{int}, \widetilde{Q}_{int}\}$$

that satisfies the following conditions in every period.

Households. The household budget constraint, the Euler equation (3) and the portfolio condition (4) hold, together with the transversality condition

$$\lim_{t\to\infty} \beta^t \frac{K_{it+1} + S_{it+1}^v}{C_{it}} = 0$$

and

$$R_{it+1}^k = 1 - \delta_K + r_{it+1}^K, \qquad R_{it+1}^v = \nu_{it+1}.$$

Firms. Output, wages and the rental rate are as in Appendix A.1. Capital demand in period t equals the stock K_{it} that households chose in period $t-1$. Dividends satisfy (7).

Innovation. Innovation follows (A.1), country productivity follows (8) and the frontier follows (9). Patent values satisfy the recursion for v_{it} in Appendix A.2 and returns satisfy (12).

VC. Portfolio shares satisfy (13), origin returns (14), financial flows (15), and destination payments (17).

Goods market. The final good is freely traded, so the resource constraint (18) holds at the world level. Management fees are a real resource cost. Financial VC flows are spent on R&D in full: the iceberg friction τ_{in} reduces the effective R&D they buy, not the resources they use.

This constraint is implied by the household budgets and the other conditions, by Walras' law. Summing the budget constraints over countries and using (7) gives

$$\sum_i \left[C_{it} + K_{it+1} + S^v_{it+1} + f_{it}\right] = \sum_i \left[W_{it}L_i + R^k_{it}K_{it} + \Pi_{it}\right] + \sum_i R^v_{it}S^v_{it} - \sum_n \rho_{nt}Q_{nt-1}.$$

Summing (17) over destinations, with $\sum_n z_{int-1} = 1$, shows that the last two sums cancel: what origins earn on VC equals what destinations pay. Using $R^k_{it} = 1 - \delta_K + r^K_{it}$ and $W_{it}L_i + r^K_{it}K_{it} + \Pi_{it} = Y_{it}$ from Appendix A.1 then gives (18).

A.5 Balanced growth path

Normalized variables are $x_i \equiv X_{it}/\bar{A}_t$. Stocks are normalized by the frontier of the period in which they are held, so $s^v_i = S^v_{it}/\bar{A}_t$, $k_i = K_{it}/\bar{A}_t$, $S^v_{it+1}/\bar{A}_t = g\, s^v_i$ and $K_{it+1}/\bar{A}_t = g\, k_i$.

The BGP is the solution of (19), (20), (21) and (23), together with the innovation rate, the allocation (13) and return (14) without time subscripts, and destination payments

$$\rho_n q_n = g \sum_{i=1}^{N} z_{in}\, R^v_i\, s^v_i, \tag{A.2}$$

which normalize (17). The right-hand side is what origins must earn, which is the return R^v_i times the financial flow $g\, z_{in} s^v_i$. The rest of the system follows.

Capital and output. The common rental rate in (20) gives k_i from $r^K = (\alpha/\mu)(a_i L_i/k_i)^{1-\alpha}$, and output is $y_i = (a_i L_i)^{1-\alpha} k_i^{\alpha}$.

Consumption and dividends. The normalized budget constraint gives

$$
\begin{aligned}
c_i &= (1-\alpha)y_i + R^k k_i + R_i^v s_i^v + d_i - g\,(k_i + s_i^v) - f_i, \\
d_i &= \frac{\alpha(\mu-1)}{\mu} y_i - \frac{\rho_i q_i}{g}, \\
f_i &= \frac{\varphi_i}{1+\zeta}\left(\frac{g\,s_i^v}{y_i}\right)^{1+\zeta} y_i.
\end{aligned}
$$

The goods market clears, $\sum_i y_i = \sum_i \left[c_i + (g - 1 + \delta_K)k_i + g\,s_i^v + f_i\right]$, by Walras' law.

Interior BGP. An interior BGP requires, for every i,

$$
\eta_i > 0, \qquad \eta_i + b_i \leq 1, \qquad \sum_n \eta_n \leq 1, \qquad s_i^v > 0, \qquad R_i^v > \frac{g}{\beta}, \qquad \frac{g}{\beta} > 1 - \eta_i - b_i, \qquad d_i \geq 0,
$$

and $1/\gamma + \sigma < 1$. The condition $R_i^v > g/\beta$ is required for $\varphi_i > 0$. The condition $d_i \geq 0$ requires local profits to cover the payments to VC investors.

Break-even condition with a common return. Substituting (21) into (A.2) gives $(\kappa/\gamma)\eta_n v_n = g\sum_i z_{in} R_i^v s_i^v$. If all origins earned the same VC return R^v, the gross financial inflow into n would be

$$
g\sum_i z_{in} s_i^v = \frac{1}{R^v}\,\frac{\kappa}{\gamma}\,\eta_n v_n,
$$

so destination inflows would be proportional to the value of the patents a destination creates. With heterogeneous participation costs, origin returns differ and the mapping holds only approximately.

A.6 Social return to VC

The externality in (1) means that research in period t also raises the productivity of research in $t+1$, and entrepreneurs do not take this into account. Consider one more unit of R&D in location n in period t, holding Y_{nt} and research in $t+1$ fixed. Its private value at $t+1$ is ρ_{nt+1}. In addition, (A.1) implies

$$
\frac{\partial \eta_{nt+1}}{\partial Q_{nt}} = \sigma\,\frac{\eta_{nt+1}}{Q_{nt}}.
$$

Each new patent created in $t+1$ is worth $\kappa v_{nt+2}\bar{A}_{t+1}$ at $t+2$, which is discounted to $t+1$ at $R^k = g/\beta$. On the BGP, with $\bar{A}_{t+1} = g\bar{A}_t$ and constant η_n and v_n, the additional value at $t+1$ is

$$
\sigma\,\frac{\eta_n}{Q_{nt}}\,\kappa v_n\,g\bar{A}_t\,\frac{\beta}{g} = \beta\sigma\,\frac{\eta_n}{Q_{nt}}\,\kappa v_n \bar{A}_t = \beta\gamma\sigma\,\rho_n,
$$

where the last step uses (12). Adding the private value gives (22). Since Q_{nt} enters the externality only with a one-period lag, the calculation counts only this direct spillover in the next period. This values the extra innovation at the private value of a patent, so it is a return in patent values and not a full welfare calculation.

A.7 Market size and the value of a patent

This subsection derives (32). The case $\lambda = 1$ is a single market in each location. The case $\lambda = 0$ is the one in which the number of markets rises one for one with population, so that market size does not vary across locations. This is the benchmark in models where free entry makes the number of firms proportional to population (Trouvain, 2026), and in Buera et al. (2026), where a larger country has more locations of the same size, so population does not raise the incentive to innovate directly.

Sub-markets. Each product line $j \in [0,1]$ is divided in location i into N_i sub-markets, indexed by s, and labor is split equally across them, so each sub-market has L_i/N_i workers. I set

$$N_i = L_i^{1-\lambda}, \qquad 0 \leq \lambda \leq 1, \tag{A.3}$$

with L_i normalized to have a sample mean of one. Labor per sub-market is then $L_i/N_i = L_i^{\lambda}$. A larger population raises the size of each sub-market when $\lambda > 0$. When $\lambda = 0$ it raises only the number of sub-markets. In locations below the sample mean $N_i < 1$, which I read as a patent whose market extends beyond the location.

Production. Final output is

$$Y_{it} = \left(\frac{L_i}{N_i}\right)^{1-\alpha} \int_0^1 \int_0^{N_i} \left(A_{it}^{js}\right)^{1-\alpha} \left(x_{it}^{js}\right)^{\alpha} ds\, dj.$$

With limit pricing, as in Section 3, demand and profits in a sub-market are

$$x_{it}^{js} = A_{it}^{js} \frac{L_i}{N_i} \left(\frac{\alpha}{\mu r_{it}^K}\right)^{\frac{1}{1-\alpha}}, \qquad \pi_{it}^{js} = \bar{\omega} A_{it}^{js} \frac{L_i}{N_i} \left(r_{it}^K\right)^{-\frac{\alpha}{1-\alpha}} = \bar{\omega} A_{it}^{js} L_i^{\lambda} \left(r_{it}^K\right)^{-\frac{\alpha}{1-\alpha}}. \tag{A.4}$$

This is where L^{λ} comes from: it is the labor one patent can sell to. Define productivity as the mean across sub-markets, $A_{it} \equiv N_i^{-1} \int_0^1 \int_0^{N_i} A_{it}^{js}\, ds\, dj$, and capital as $K_{it} \equiv \int_0^1 \int_0^{N_i} x_{it}^{js}\, ds\, dj$. Aggregating gives

$$Y_{it} = (A_{it} L_i)^{1-\alpha} K_{it}^{\alpha}, \qquad r_{it}^K K_{it} = \frac{\alpha}{\mu} Y_{it}, \qquad \Pi_{it} = \frac{\alpha(\mu - 1)}{\mu} Y_{it}.$$

These are the aggregate equations of Section 3. N_i does not appear in them.

Innovation. There is one R&D project per line and location, so η_{it} is given by (A.1). A success makes the technology $\kappa \bar{A}_t^j$ available in every sub-market of line j in location i. The law of motion (8) and the frontier (9) are therefore unchanged, and the frontier grows with $\sum_n \eta_{nt}$.

Return to innovation. A patent can be enforced in one sub-market only. Producers in the other sub-markets of the line use the technology without paying the inventor. They keep their own profits, which reach domestic households as dividends. The patent is replaced at rate $\eta_{it} + b_i$, which gives (32). The return to VC is

$$\rho_{it+1} = \frac{\kappa}{\gamma} \frac{\eta_{it}}{Q_{it}} v_{it+1} \bar{A}_t,$$

as in (12). Households still receive all of Π_{it} and pay $\rho_{it+1} Q_{it}$ for new patents.

A.8 More on the assumptions

This subsection discusses three assumptions of the model: the form of the bilateral frictions τ_{in}, the interpretation of the participation cost φ_i, and the restriction of physical capital to domestic ownership.

A.8.1 Bilateral frictions

I interpret τ_{in} as the cost of a manager's reach, and I therefore locate the friction where the VC firm operates. VC firms source deals, negotiate contracts, monitor companies and sit on their boards, and distance makes these activities more costly. Bernstein, Giroud and Townsend (2016) show that shorter travel time raises innovation and the likelihood of a successful exit at existing portfolio companies. Tian (2011) shows that VC investors located farther from a company fund it in more rounds, with shorter gaps between rounds and smaller amounts per round, which suggests that staging substitutes for direct monitoring.

The frictions take an iceberg form, so part of each dollar invested across borders does not become R&D. This is what lets lower frictions raise R&D per dollar in Section 6. If part of the estimated friction were instead a preference or a transfer between investors, removing it would save fewer resources. The estimates cannot separate these cases, since all of them lower observed flows in the same way.

The regression identifies one home effect per location and does not say whether it belongs to the investor or to the destination. I assign it to the investor. The round trip $\sqrt{\tau_{in}\tau_{ni}}$ does not depend on this choice, and it is close to the round trip inverted directly from flows when weighted by flows (Table C.3). Frictions are also held fixed over time and across counterfactuals, other than the changes each experiment imposes. Estimates

by five-year window are reported in Table C.4.

A.8.2 Participation costs

The model assumes that households reach VC through intermediaries in their own location, at a cost that differs across locations. The US retirement system offers one reason why this cost could differ even within an integrated national market. In March 2026, 70% of private industry workers had access to defined contribution plans and 14% to defined benefit plans, against 39% and 86% in state and local government.[5]

The two types of plan differ in how savings can reach private markets. In a defined benefit plan, fund managers allocate the assets. US state and local pension funds held 13.8% of their assets in private equity in 2024.[6] This category also includes buyouts and other strategies, so VC is only part of it. In a defined contribution plan, participants choose among investment options. A 2020 Department of Labor letter addressed plan sponsors' concerns about fiduciary liability and stated that offering a professionally managed fund with a private equity component would not violate fiduciary duties for that reason alone. It does not cover direct investment by participants.[7]

These rules matter for VC supply. Gompers and Lerner (1998) find that aggregate and state-level VC fundraising rise when pension investment restrictions ease. Arrangements also differ across states. For example, Alaska has offered only a defined contribution plan to all new public employees since 2006, and Michigan to new state employees since 1997.[8] Hochberg and Rauh (2013) find that public pension funds overweight private equity funds in their home state, by 9.8% of aggregate private equity investment and 16.5% for the average investor, and more so in VC than in buyouts. Chen and Ewens (2025) also find same-state overweighting in VC funds by investors such as pension funds and banks.

I therefore read φ_i as a reduced-form wedge on the effective supply of VC managed from location i, which includes the cost of channelling local savings into VC. Pension rules can affect the supply of VC, but the inversion does not identify their contribution to the estimated participation cost. Section 5.4 reports how φ_i relates to pension assets and household portfolios, which the inversion does not target.

A.8.3 Physical capital

Households in the model own only domestic physical capital. This restriction does not bind on the balanced growth path. The fee applies only to VC, so the Euler equation (3)

[5] U.S. Bureau of Labor Statistics, *Employee Benefits in the United States, March 2026*, release USDL-26-1534, Table 1.

[6] Public Plans Data, *National Data*, asset allocation for state and local pensions, fiscal year 2024.

[7] U.S. Department of Labor, Employee Benefits Security Administration, *Information Letter 06-03-2020*.

[8] National Association of State Retirement Administrators, *Defined Contribution*, accessed 5 November 2026.

gives

$$R_i^k = \frac{g}{\beta}$$

in every location. The discount factor and the growth rate are common, so the return on physical capital is the same everywhere, in the baseline and in every counterfactual. VC supply is pinned down by the portfolio condition (4), which depends on the VC return, the return on physical capital and φ_i, and not on household wealth.

VC returns still differ across locations, so free movement of physical capital would not substitute for lower VC frictions.

B Data and additional facts

I describe how I construct the VC and patent samples.

B.1 VC data from LSEG

The investment chain. In a typical VC fund, limited partners (LPs), such as pension funds, endowments and other institutional investors, commit capital to a fund vehicle. The general partner (GP), or its management company, manages the fund and selects and monitors investments in portfolio companies. The LPs, fund vehicle, manager and portfolio company can all be located in different countries. LSEG provides information on the investing firm and the fund vehicle used in a transaction, as well as the portfolio company, but does not identify the underlying LPs or their commitments. Not every investor uses this structure: corporations, individuals and other investors can invest directly.

Observations and variables. I define a deal as a unique financing round, identified by the LSEG Investment Round PermID. A company can receive several rounds, and each round can involve several investors. The raw data therefore contain multiple investor-round observations for the same deal, identified by the Investment Round Disbursement ID. I use the following information:

- **Financing rounds:** round and disbursement identifiers, investment date, investment stage, and the investor-specific amount (`Investor Equity Total`).
- **Portfolio companies:** names and aliases, founding dates, and headquarters city, country and US state. Names, aliases and founding dates also enter the link to PATSTAT described in Appendix B.3.
- **Investing firms:** names, headquarters city, country and US state, and organizational type (`Firm Investors Type`), used to apply the investor exclusions.

- **Fund vehicles:** names, identifiers, country and available state information, and the indicator for an unspecified fund. These distinguish identified vehicles from placeholder records when comparing firm and fund locations.

Sample. The LSEG module covers both VC and other private-equity transactions, including acquisitions, buyouts and secondary purchases. The baseline retains Seed, Early Stage, Expansion and Later Stage rounds, and excludes investors classified as Government Affiliated Programs or University Programs. The descriptive comparison with the broader PE/VC sample in Appendix B.2 relaxes only the investment-stage restriction.

Amounts. Monetary bilateral flows sum positive `Investor Equity Total` values by investor location, investee location and year. Amounts are in nominal US dollars and may include LSEG estimates. A financing round with no usable amount can enter deal counts but contributes no value to monetary flows. The number of investor-round observations is not the number of deals.

Amount corrections. I correct several recording errors in LSEG amounts. The 2020 Danggeun Market round, recorded at $40.3bn, is set to its reported $33m. A batch of 2019–2020 French rounds recorded about 1000 times too large is divided by 1000. The amounts of two 2021 French rounds recorded about 100 times above comparable rounds by the same investor are set to zero. I also exclude the 2021 BrainTrip round in Malta, whose LSEG-estimated amount is implausibly large, following the sample used in the descriptive charts.

Investor location. I use the investing firm's headquarters as its origin, recorded in `Firm Investors Nation` and the corresponding state fields for US investors. For a fund-managed investment, this is the recorded location of the GP or management company. Using the fund vehicle instead can change the recorded origin even though the manager and portfolio company are unchanged. Neither field identifies the residence of the LPs supplying the capital.

I compare this rule with one that uses the fund's location whenever LSEG records it. In the all-stage PE/VC sample over 2000–2024, among strictly identified fund vehicles, firm and fund countries coincide for 90.7% of investment value. Under the fund-preferred rule, which uses fund location where available, Luxembourg loses $9.8bn (25.7%) of attributed investment, largely through CVC funds recorded in the UK. Sweden loses $4.7bn (10.5%), mainly through EQT funds recorded in the UK. China, Hong Kong and Japan gain $27.9bn, $18.7bn and $18.6bn, respectively, as investments by US- and UK-based managers are reassigned to their Asian funds. These are changes in the recorded origin of investment, not changes in where portfolio companies receive it. The venture sample over

2000–2024 shows the same thing from the destination side. EU27 startups receive 43.5% of their investment from investors in their own country under both rules, and 23.9% from the US. The UK share falls from 10.6% to 9.9%. One reason the two rules agree so often is that most disbursements carry a placeholder fund, such as "Undisclosed Fund", whose recorded location copies the investor firm's.

B.2 Sample characteristics

The baseline VC sample. Table B.1 describes financing rounds for portfolio companies in the EU27 and the US over 2000–2024. It includes all investor origins and uses the stage and investor restrictions in Appendix B.1. The geographic sample therefore covers the full EU27 and US, independently of the locations retained in the quantitative model.

Table B.1: VC sample characteristics by portfolio-company location, 2000–2024

	EU27	United States
Financing rounds	38,254	126,793
Investor-round observations	90,767	383,913
Distinct portfolio companies	23,697	50,962
Investment (USD bn)	279.1	1,761.4
Median round value (USD m)	2.7	5.0
Round value, 25th percentile (USD m)	0.9	1.8
Round value, 75th percentile (USD m)	7.7	14.0
Syndicated rounds (%)	52.0	62.6
Rounds with positive recorded amounts (%)	67.6	87.4
Estimated share of investment value (%)	83.4	84.8

Notes: Geography is the portfolio company's country. EU27 excludes the UK. The sample retains Seed, Early Stage, Expansion and Later Stage rounds and excludes government-affiliated and university-program investors. All investor origins are included, including missing origins. Round values sum positive investor-specific LSEG amounts from retained investors, in nominal US dollars, including estimates. Quantiles condition on positive round value. Amounts incorporate the corrections described in B.1, and the BrainTrip 2021 round is excluded. Syndication means more than one distinct recorded investor key in a round. Anonymous investor observations without an identifier receive separate keys, as in the supporting tables. Estimated value is the share of positive amounts flagged as estimated by LSEG.

The EU27 sample contains 38,254 rounds involving 23,697 companies, compared with 126,793 rounds and 50,962 companies in the US. Conditional on a positive recorded amount, the median round is \$2.7m in the EU27 and \$5.0m in the US. Syndicated rounds account for 52.0% and 62.6% of rounds, respectively. Positive amounts are available for 67.6% of EU27 rounds and 87.4% of US rounds. LSEG estimates account for 83.4% and 84.8% of recorded investment value. Differences in amount availability should therefore be kept in mind when comparing the two regions.

Figure B.1 compares stage composition using financing-round counts and investment amounts. Each round counts once in panel a, including rounds without a positive recorded amount. Panel b uses positive investor-specific amounts, including LSEG estimates. Seed

rounds account for 10.8% of EU27 rounds and 7.8% of US rounds, but only 3.0% and 4.1% of investment value. Later Stage rounds account for 14.1% of EU27 rounds and 19.8% of US rounds, and about 29% of investment value in both regions.

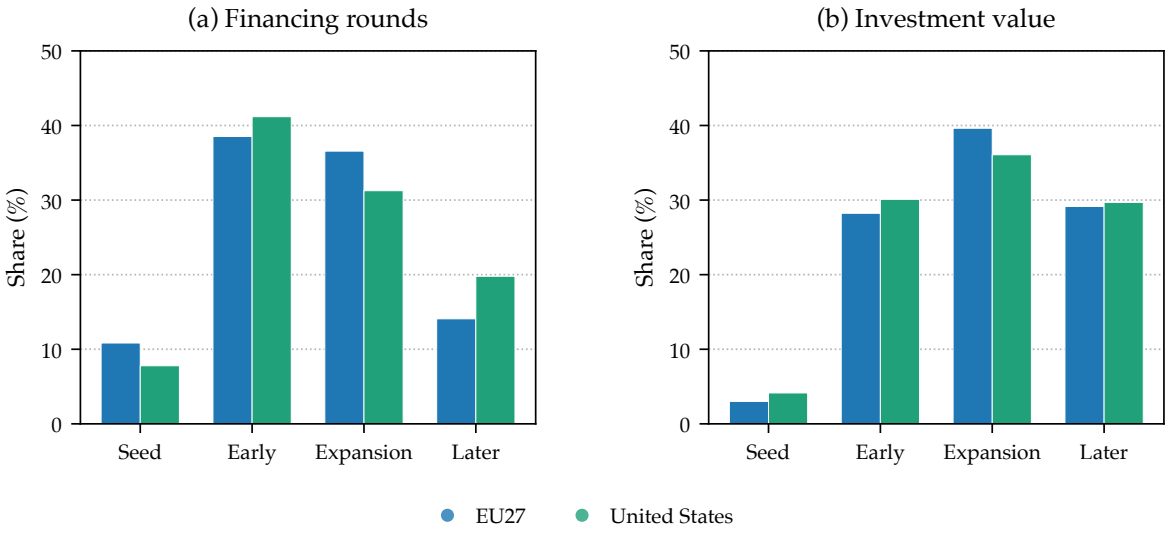


Figure B.1: VC stage composition by portfolio-company location, 2000–2024

Notes: Shares sum to 100 within each region and panel. Geography, sample restrictions and amount corrections are as in Table B.1. Round-count shares include rounds without a positive recorded amount. Investment shares use positive amounts from retained investors in nominal US dollars, including estimates.

The broader PE/VC sample. Retaining all investment stages increases the sample to 66,138 rounds and $632.2bn in the EU27, and 209,541 rounds and $3,199.1bn in the US (Table B.2). The VC stages retained in the baseline account for 57.8% of EU27 rounds and 60.5% of US rounds, but 44.2% and 55.1% of investment value. These shares compare VC stages with the full PE/VC module, holding the investor exclusions fixed.

Table B.2: The broader PE/VC sample, 2000–2024

	EU27	United States
Financing rounds, all PE/VC stages	66,138	209,541
Investment, all PE/VC stages (USD bn)	632.2	3,199.1
Median round value, all PE/VC stages (USD m)	3.0	5.2
VC stages, share of all rounds (%)	57.8	60.5
VC stages, share of all investment (%)	44.2	55.1

Notes: The broader sample retains all LSEG PE/VC investment stages, including VC. Both samples exclude government-affiliated and university-program investors and use the same target geography, years and amount treatment as Table B.1. The broader sample also includes the two additional French-batch corrections that occur outside VC stages. VC shares use all rounds or all positive investment amounts in the broader sample as their respective denominators. Median round values condition on a positive recorded amount. Values include LSEG estimates.

Figure B.2 shows annual investment received by portfolio companies in the EU27, the US and the UK over 1990–2024. Panel a uses the baseline VC stages, and panel b includes all PE/VC stages. Both panels use current US dollars and the same investor exclusions and amount corrections as the summary tables. The 1990–1999 observations come from the harmonized historic LSEG download, and the EU27 and US series from 2000 onward reproduce the totals used above.

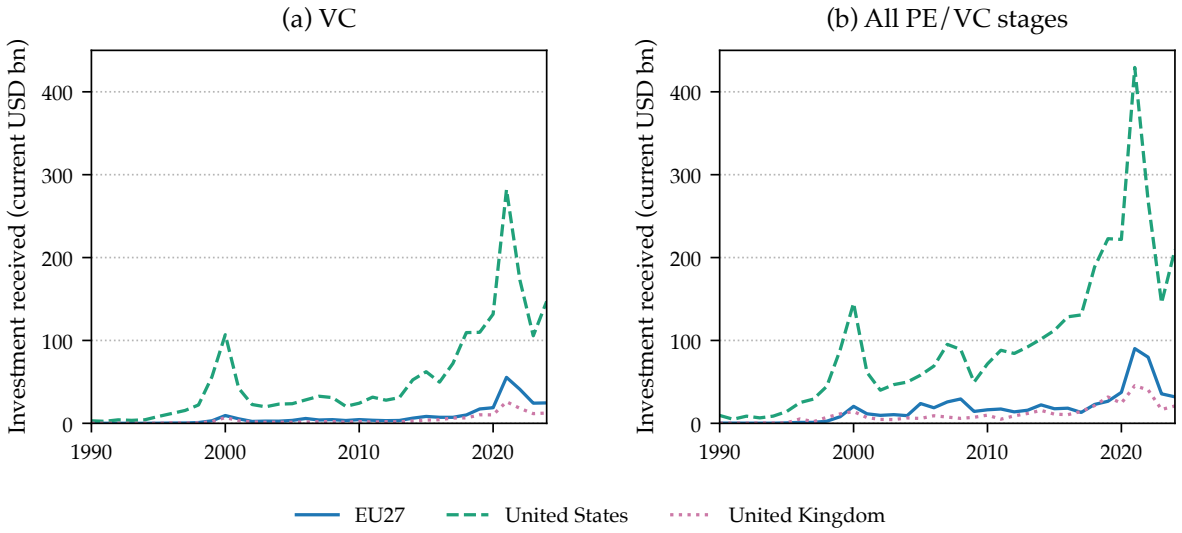


Figure B.2: Annual VC and PE/VC investment received, EU27, US and UK, 1990–2024

Notes: Geography is the portfolio company's country. EU27 excludes the UK. Investment sums positive investor-specific amounts from all investor origins, including missing origins, in nominal US dollars. LSEG estimates are included. VC comprises Seed, Early Stage, Expansion and Later Stage rounds. The all-stage PE/VC total includes VC. Both panels exclude government-affiliated and university-program investors and apply the amount corrections and BrainTrip exclusion described in Appendix B.1. The panels share the same vertical scale.

B.3 Patent data and the link to LSEG

Source and scope. Patent data come from PATSTAT Global (Autumn 2025 edition). PATSTAT and LSEG share no firm identifier, so I link them by name. The match covers LSEG investee firms in 31 countries: the EU27, the UK, Norway, Switzerland and the US. The PATSTAT side contains applicants whose PSN sector is company or unknown. I keep the unknown category because its share varies by country and is largest in France, so dropping it would undercount French patents in particular. The procedure is similar to the one used to link the OECD Start-ups Database to patent data (Berger et al., 2026): names are harmonized with country-level dictionaries and then matched within country.

Matching stages. I match each LSEG name and its LSEG-supplied aliases to PATSTAT applicant names in stages, from the most to the least conservative.

1. **Exact match** on names cleaned of case, punctuation and spacing, within the same country.

2. **Exact match after country-specific name rules**, which standardize or drop legal forms and common name variants. I start from a dictionary of national legal forms and review it against the Entity Legal Form code list published by GLEIF (ISO 20275). For the US, I also use the legal-form rules of the NBER/Derwent name standardization routine. Firms accepted in the first stage also collect any applicants found in this stage, so that a firm filing as both "Ltd" and "Limited" keeps both. Cleaned names shorter than four characters are accepted only after case-by-case review.

3. **Fuzzy match** within country. A pair must have Levenshtein and Jaro-Winkler similarity of at least 0.85, binary trigram cosine similarity of at least 0.90, and the same first character.

In every stage, I reject an applicant if its earliest patent filing predates the firm's LSEG founding date. If either date is missing, the applicant is kept. This keeps out the older patents of namesakes and acquirers. Table B.3 reports the result.

Table B.3: LSEG firms linked to PATSTAT, within country

Stage	Firms	Share
Exact	40,479	23.4%
Exact, country rules	10,146	5.9%
Exact, short names reviewed	602	0.3%
Fuzzy	364	0.2%
Linked within country	51,591	29.9%
Not linked	121,040	70.1%
All firms	172,631	100%

Links across countries. The stages above miss startups that patent through a foreign entity. I therefore add a foreign applicant when four conditions hold: (i) its name, without legal forms, equals the firm's and is distinctive, (ii) at least one of its inventors lives in the firm's country, or it shares an inventor with the firm's existing patents, (iii) its first filing does not predate the firm's founding, and (iv) it has no more than the larger of 20 patent families and three times the firm's matched families. The last condition excludes multinational parents of local subsidiaries that LSEG lists as separate firms. After a case-by-case review of 126 entities, this step adds 3,298 foreign entities for 2,826 firms, of which 340 had no link before. The final crosswalk links 51,931 firms to 352,629 PATSTAT person identifiers.

Family counts. I count each DOCDB family once, even when the invention is filed at several offices, following Berkes, Manysheva and Mestieri (2022). I use patents for invention only, which excludes utility models and other non-invention rights. I keep a family if it has a grant at the EPO or the USPTO. A family granted only at other offices is kept if one of those offices examined inventive step when the application was filed, and if no other DOCDB family in the same INPADOC family has a grant at the EPO or the USPTO, since such a family would be the same invention under a different priority set. I date each family by the filing date of its earliest application for invention. A family is split equally across the distinct organizational applicants on that application, excluding applicants who are also listed as inventors, because US filings before the America Invents Act list inventors as applicants. If the application names no organization, the family is split across all its applicants.

Assignment to firms and locations. A family counts for a firm if the firm's first qualifying VC round is in 1995 or later, and each firm is assigned to the location of that round. I exclude incumbents: firms founded at least 20 years before their first round, or with at least 20 families filed at least five years before it. Patents filed before the first round count, because LSEG may miss early rounds. They are 18% of counted families in Europe and 9% in the US. The resulting sample has 141,751 fractional patents filed in 2000–2019 across the 64 locations used for the patent checks.

Alternative measures. Location shares change little under other definitions. I build a revised count that drops the examination and INPADOC filters and keeps every family with a grant at any office. It dates each family by its earliest priority date, or by its earliest filing date if no priority date is available. It splits a family across the distinct organizational applicants on the family's earliest application that names an organization, and I search all applications in the family for this. Families with no organizational applicant on any application, fewer than 0.1% of the total, are not assigned to a firm. This count has 156,301 fractional patents, and the correlation of its log shares with the baseline is 0.999. The US share is 80.0% against 81.3% in the baseline, and the EU27 share is 15.4% against 14.1%. Relative to the revised count, the correlation of log shares is 0.999 when I keep only families with a grant at the EPO or USPTO, and 0.998 when I keep all families regardless of grant status.

Citation-weighted counts. The baseline is the unweighted count. As an alternative measure that accounts for differences in patent quality, I build citation-weighted counts on the revised count, adapting Hall, Jaffe and Trajtenberg (2005) and Bernstein, Giroud and Townsend (2016) to DOCDB families. For each family, I count the distinct DOCDB families that cite any of its applications and whose earliest priority date falls within three

years after the family's first grant at any office. I cap this count at the 99th percentile for the family's first-grant year and most common four-digit IPC class, computed over all granted families in PATSTAT, and divide by the capped mean of that group. A family with no citations has a weight of zero, and so does a family whose three-year window ends after the last publication in the data. The correlation of log shares with the revised count is 0.987. Figure B.3 shows that the shift is broad. Most US nodes lie above the 45-degree line, and all EU27 nodes but one lie below it. Citation weights shift shares toward the US, from 80% to 86%, while the EU27 falls from 15% to 10%. Most of this shift comes from citations in US filings: when I rebuild the weights without citing families that have an application at the USPTO, the EU27 share stays at 15%. These data cannot separate a preference for citing local work from differences in patent quality.

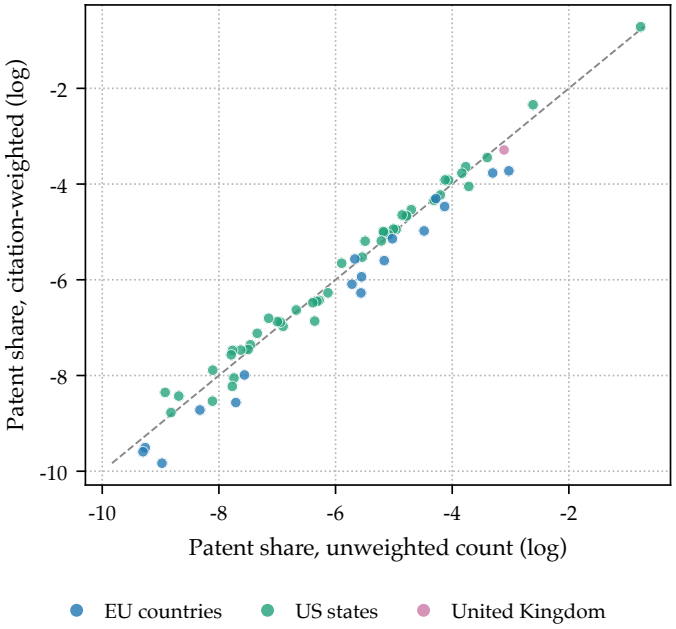


Figure B.3: Unweighted and citation-weighted patent shares by node, 2000–2019

Notes: Each dot is one of the 64 model nodes. The horizontal axis is the log share of the node in the revised unweighted count of patent families, 2000–2019. The vertical axis is the log share under the three-year citation weights. The dashed line is the 45-degree line. Nodes above the line gain share when patents are weighted by citations. The correlation is 0.987.

Match quality. Among the 94,390 firms in the 64 locations with a first round in 1995 or later, excluding incumbents, 28% of EU27 firms link to a PATSTAT applicant, compared with 25% in the UK and 37% in the US. The shares with a counted patent are 14%, 13% and 21%. A low link rate can reflect either no patenting or a failed match. To separate the two, I audit all 361 firms with a VC round in 1997–2019 in Bulgaria, Greece, Croatia, Lithuania, Malta, Romania and Latvia, of which 356 have no counted patents. I found one clear missed match in the audit. For 251 firms no applicant has a similar name, and I found no relevant patents in the 20 of them, chosen at random, that I searched manually.

B.4 Additional charts

The first three groups of charts use the VC-filtered sample. The last group repeats the comparisons on all LSEG investment stages and investor types.

B.4.1 Destination shares

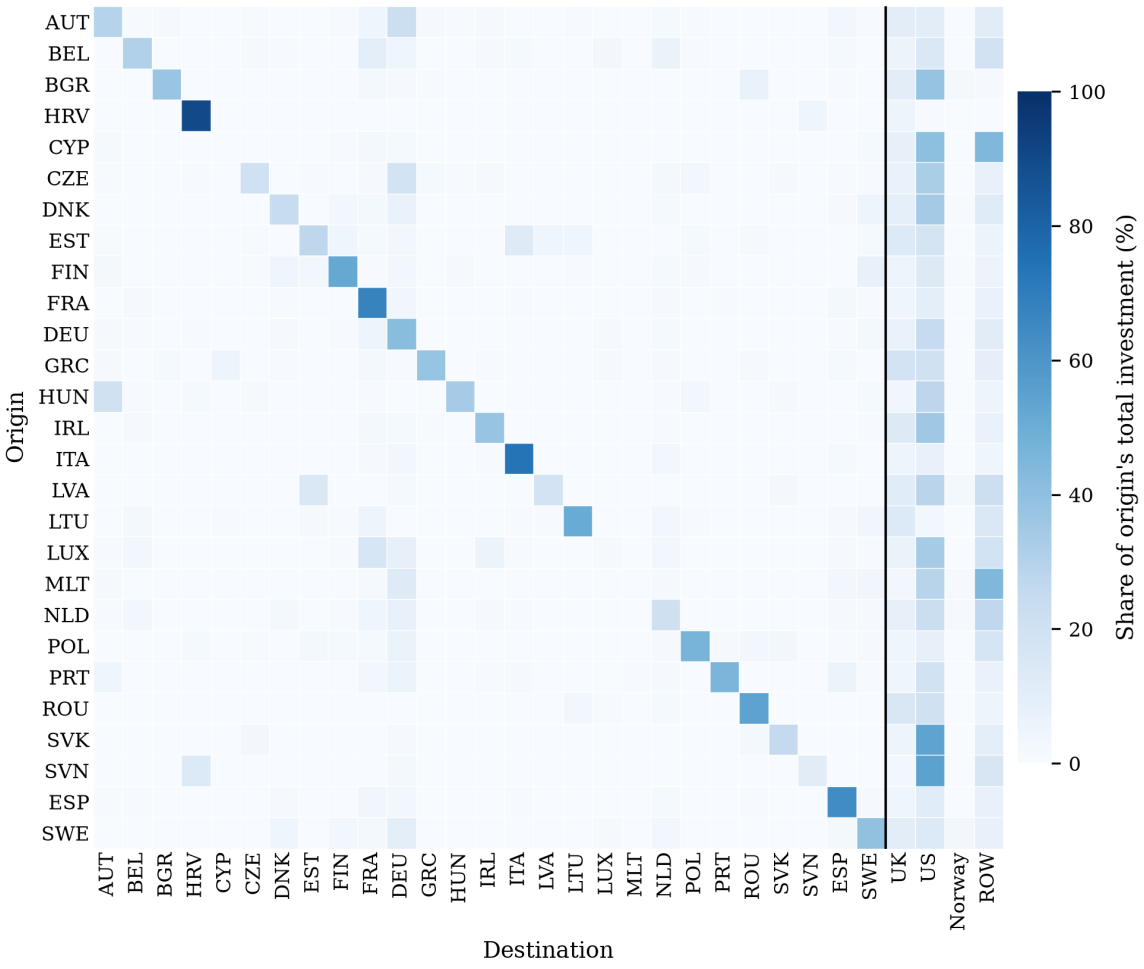


Figure B.4: Origin portfolio shares by amount, EU27 investors, 2000–2024: VC-filtered sample

Notes: Rows are investor-firm countries in the EU27 and columns are target locations. Each cell is the destination's percentage share of the origin's total investment, so each row sums to 100. Columns to the right of the vertical line are destinations outside the EU27: the United Kingdom, the United States, Norway, and the rest of the world (ROW, every other country, including Switzerland). Amounts are strictly positive investor-specific LSEG amounts over Seed, Early Stage, Later Stage and Expansion rounds, excluding government-affiliated and university-program investors. Investors whose identity is undisclosed in LSEG ("Undisclosed Firm") are excluded because they have no location.

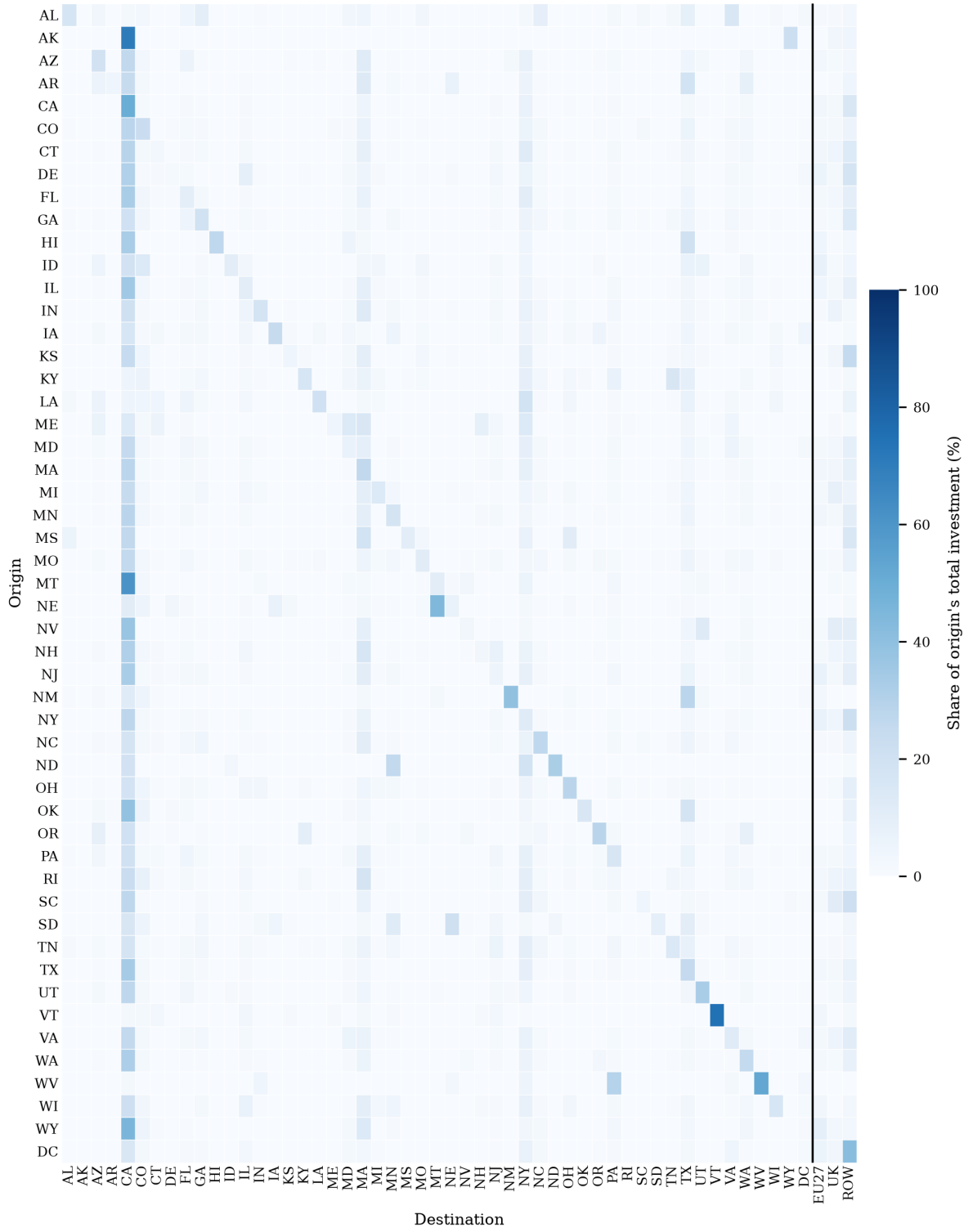
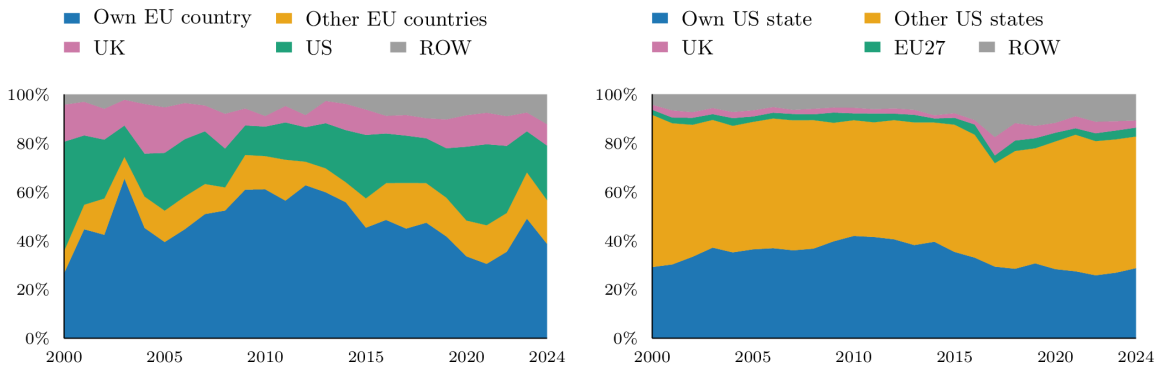


Figure B.5: Origin portfolio shares by amount, US investors, 2000–2024: VC-filtered sample

Notes: Rows are investor-firm states (plus DC) and columns are target locations. Each row sums to 100. Columns to the right of the vertical line are destinations outside the United States: the EU27 as one block, the United Kingdom, and the rest of the world (ROW). Same amounts and exclusions as Figure B.4. Excluding undisclosed investors matters most for Delaware, where 98% of the investor records with a positive amount are such undisclosed investors.

B.4.2 Sources of investment received



a) EU27 Startups b) US Startups

Figure B.6: Investor source shares over time, 2000–2024

Notes: LSEG financing rounds, 2000–2024. The sample retains Seed, Early Stage, Later Stage, and Expansion rounds and excludes government-affiliated and university-program investors.

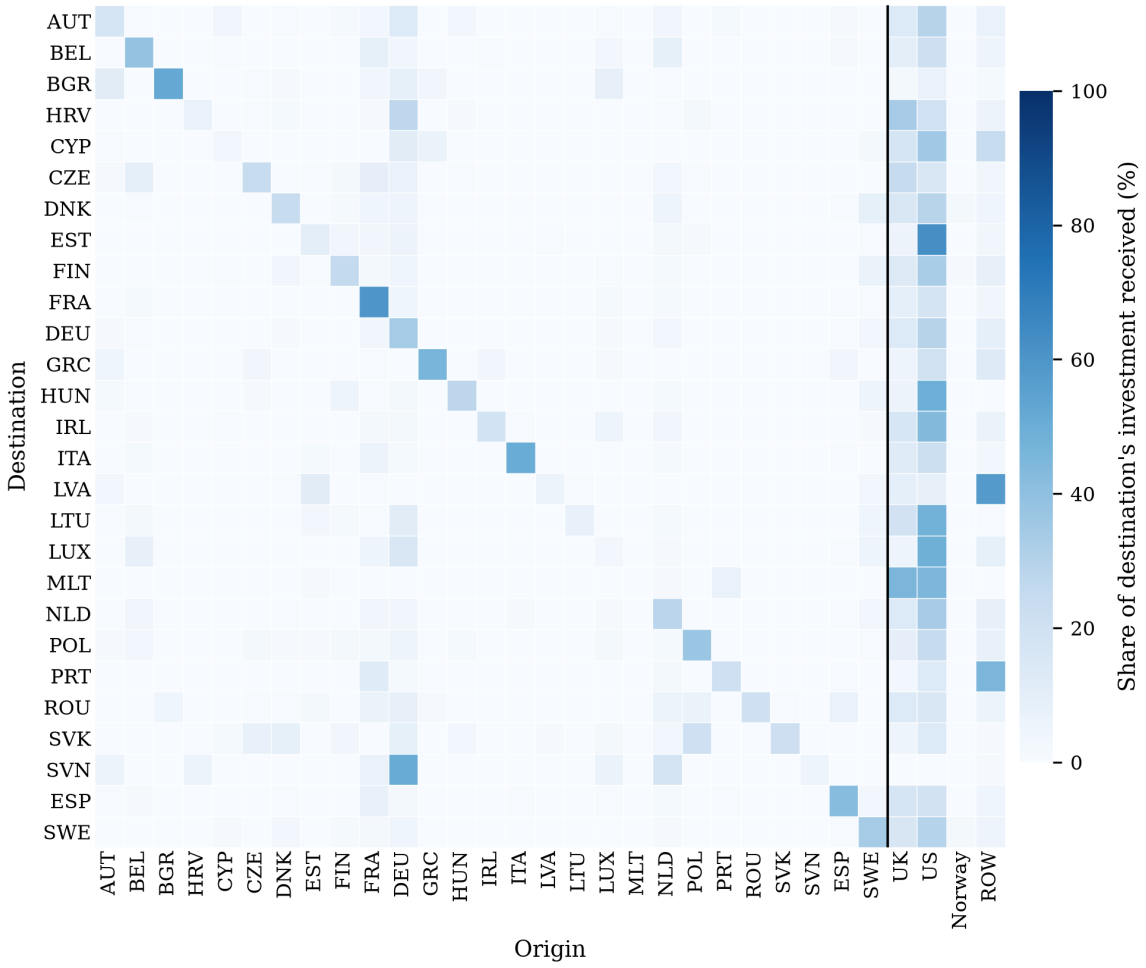


Figure B.7: Sources of investment received, by amount, EU27, 2000–2024: VC-filtered sample

Notes: Rows are target locations and columns are investor origins: each cell is the share of the destination's total investment received that comes from that origin, so each row sums to 100. Columns to the right of the vertical line are outside the EU27: the United Kingdom, the United States, Norway and the rest of the world (ROW, including Switzerland). Amounts are strictly positive investor-specific LSEG amounts. Sample: Seed, Early Stage, Later Stage and Expansion rounds, excluding government-affiliated and university-program investors. Investors recorded as "Undisclosed Firm" are excluded because they have no location.

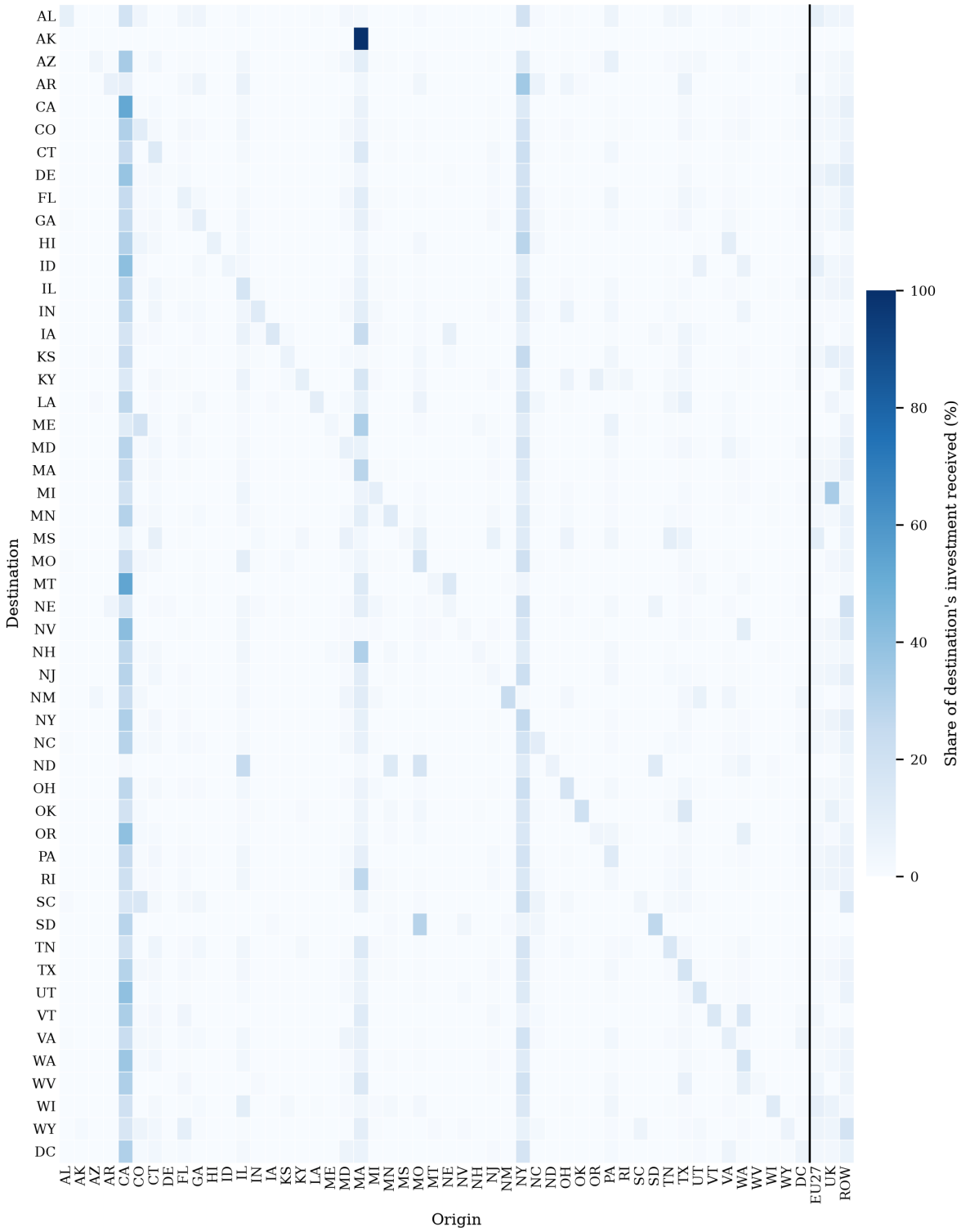


Figure B.8: Sources of investment received, by amount, US states, 2000–2024: VC-filtered sample

Notes: Rows are target locations and columns are investor origins: each cell is the share of the destination's total investment received that comes from that origin, so each row sums to 100. Columns to the right of the vertical line are outside the United States: the EU27 as one block, the United Kingdom and the rest of the world (ROW). Amounts are strictly positive investor-specific LSEG amounts. Sample: Seed, Early Stage, Later Stage and Expansion rounds, excluding government-affiliated and university-program investors. Investors recorded as "Undisclosed Firm" are excluded.

B.4.3 Home bias and concentration

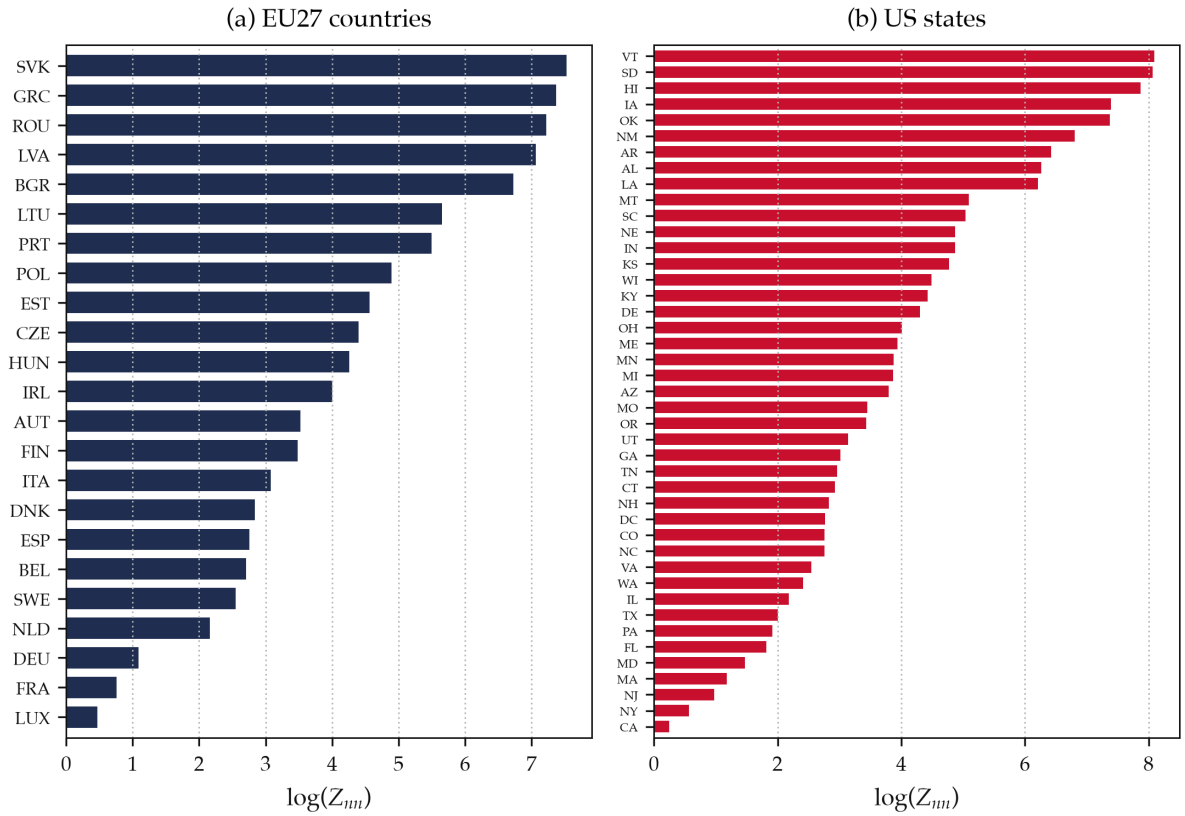


Figure B.9: Home bias using the capital benchmark, 2015–2019: $\log(Z_{nn})$

Notes: LSEG financing rounds, VC-filtered sample. Z_{nn} compares the domestic share of VC received, Q_{nn}/Q_n, with the location's share of VC invested in its block, S_n/S. Amounts are positive investor-specific amounts, with the corrections in Appendix B.1. Investors recorded as "Undisclosed Firm" are excluded because they have no location. Locations with no domestic flow in the window are not shown. EU27 excludes the UK.

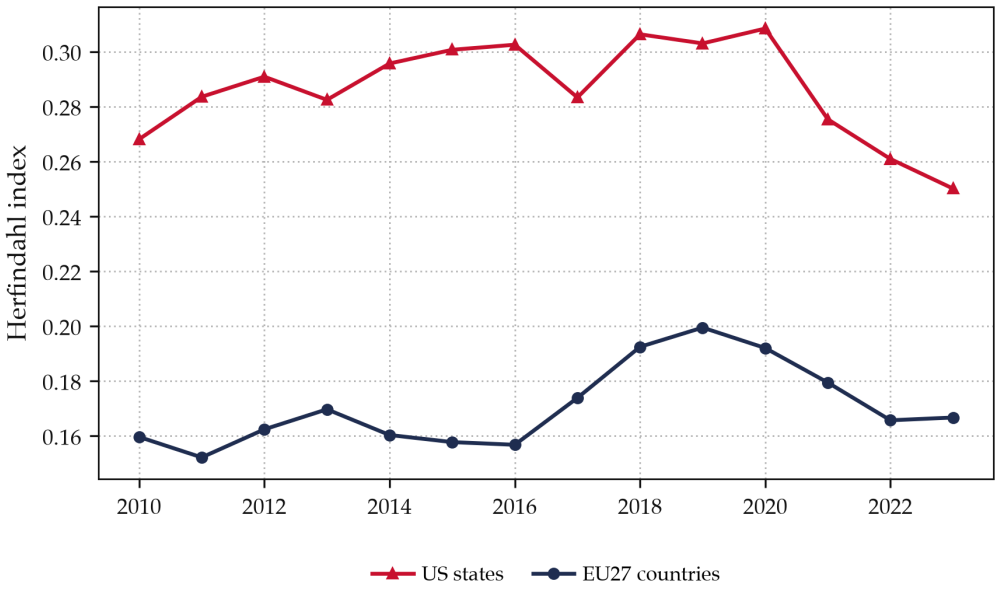


Figure B.10: Concentration over time: Herfindahl index of VC across locations

Notes: LSEG financing rounds, VC-filtered sample. Each point uses the three-year window ending in that year, 2010–2023. Higher values indicate more spatial concentration of VC received across states (US) or countries (EU27). Amounts are positive investor-specific amounts, with the corrections in Appendix B.1.

B.4.4 All types of private equity

These charts report broader-sample comparisons with the VC-filtered figures. They use all LSEG investment stages and all investor types, with the windows specified in their notes.

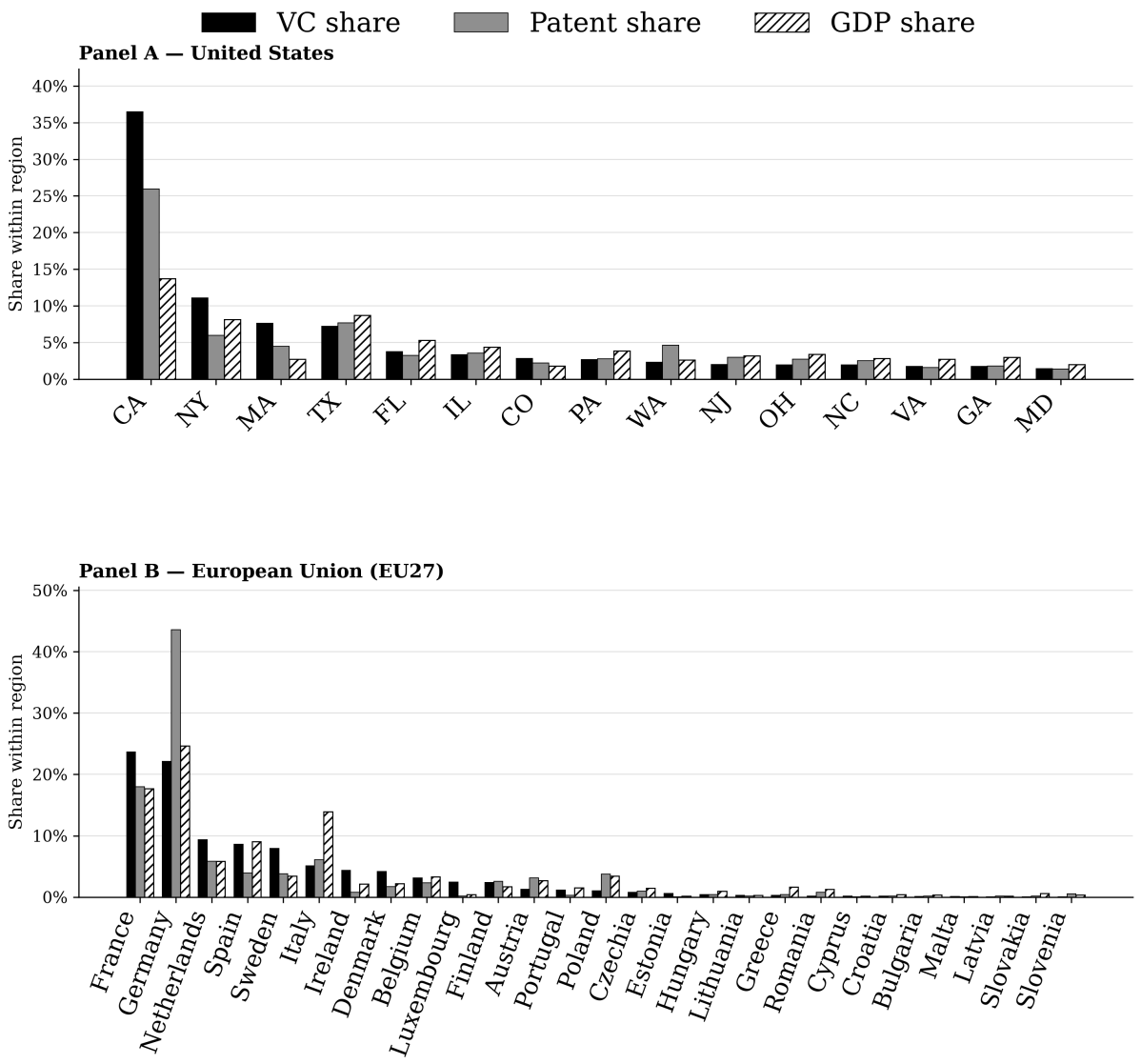


Figure B.11: Spatial concentration of VC, patenting and GDP, 2000–2024: all-PE sample

Notes: Shares are normalized within each region. VC share: sum of strictly positive investor-specific LSEG amounts (Investor Equity Total, USD) received by target companies in each location, 2000–2024, over all LSEG investment stages and all investor types. Disbursements without a disclosed amount do not enter. Patent share: granted DOCDB invention families with earliest filing year 2000–2023, split equally across all distinct inventors worldwide and assigned to the inventor's country, or to the US state when the inventor's state is unique. GDP share: mean current-price GDP 2000–2024 in US dollars, from BEA (SAGDP2) for US states and the World Bank (NY.GDP.MKTP.CD) for EU27 countries. Panel A shows the top 15 states by VC share out of the 50 states (DC excluded). Panel B shows all EU27 countries (UK excluded). California receives 36.5% of US investment, and California, New York and Massachusetts together 55.2%. In the EU27, France and Germany receive 25.2% and 21.7%.

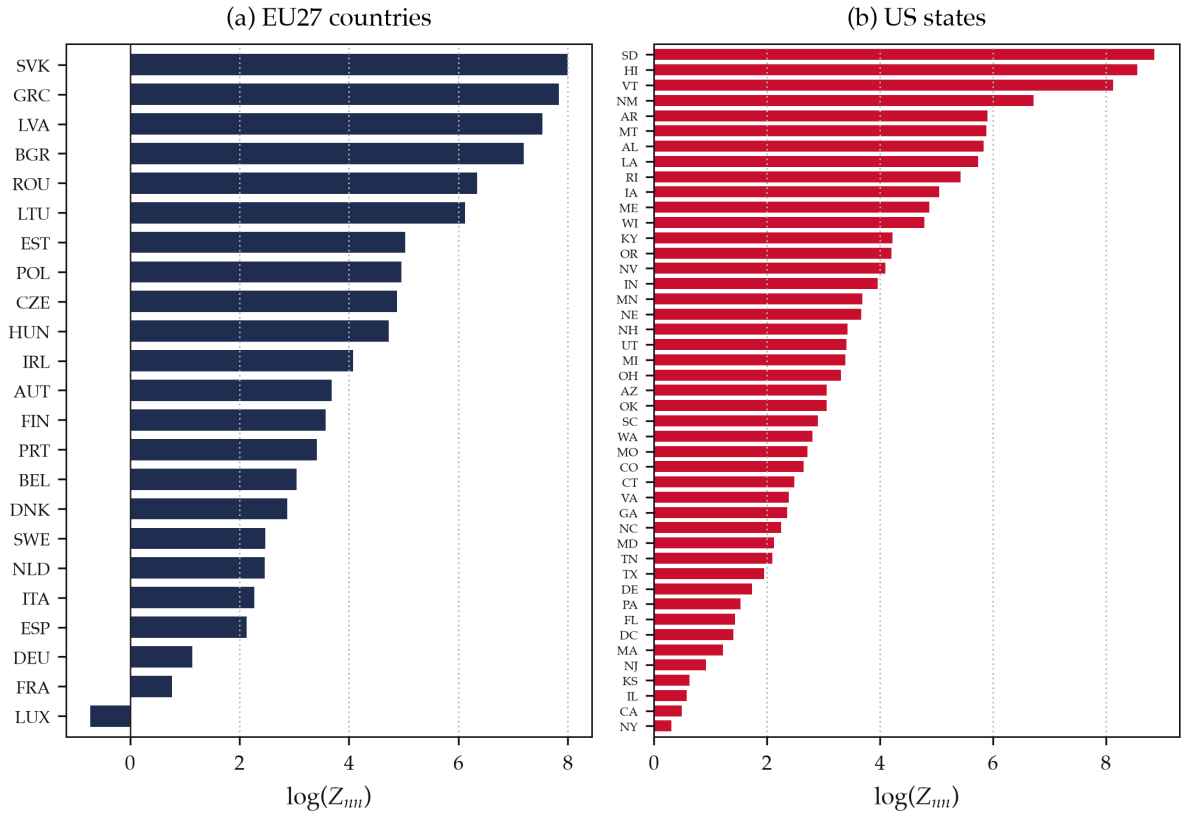


Figure B.12: Home bias using the capital benchmark, 2015–2019, all PE types: $\log(Z_{nn})$

Notes: LSEG financing rounds, all investment stages and investor types. Z_{nn} compares the domestic share of VC received, Q_{nn}/Q_n, with the location's share of VC invested in its block, S_n/S. Amounts are positive investor-specific amounts, with the corrections in Appendix B.1. Investors recorded as "Undisclosed Firm" are excluded because they have no location. Locations with no domestic flow in the window are not shown. EU27 excludes the UK.

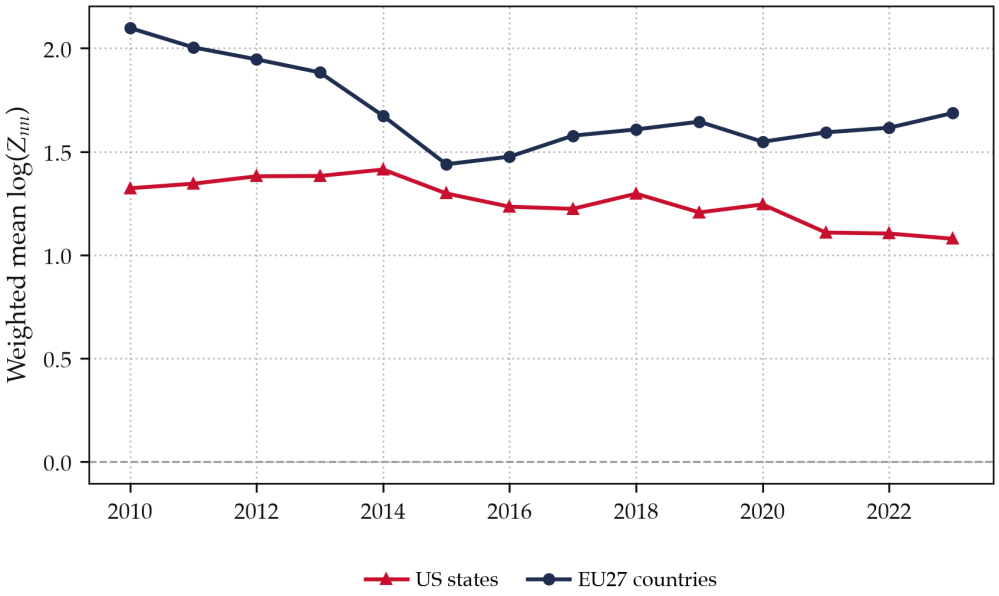
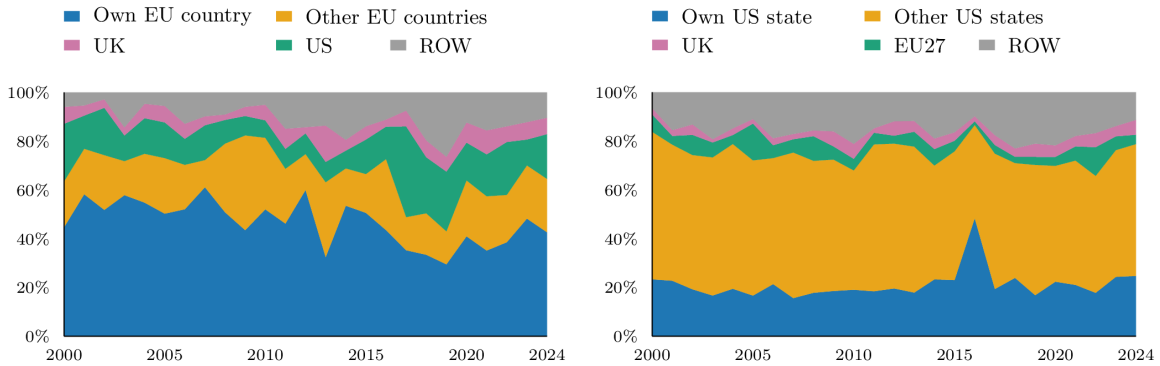


Figure B.13: Home bias over time, all PE types: weighted average $\log(Z_{nn})$

Notes: LSEG financing rounds, all investment stages and investor types. Each point uses the three-year window ending in that year, 2010–2023. Z_{nn} compares the domestic share of VC received, Q_{nn}/Q_n, with the location's share of VC invested in its block, S_n/S. Locations are weighted by VC received from their block. Amounts are positive investor-specific amounts, with the corrections in Appendix B.1. Investors recorded as "Undisclosed Firm" are excluded because they have no location.

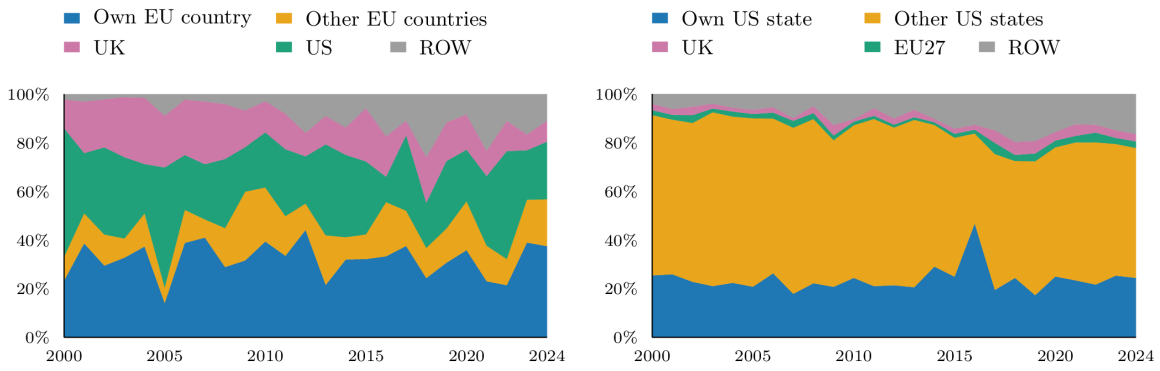


a) EU27 investors

b) US investors

Figure B.14: Investment shares by destination, 2000–2024, all PE/VC stages

Notes: LSEG financing rounds, 2000–2024. All investment stages and all investor types are included. Recording errors in LSEG amounts are corrected: the 2020 Danggeun Market round, recorded at $40.3bn, is set to its reported $33m. A batch of 2019–2020 French rounds recorded about 1000 times too large is divided by 1000. The amounts of two 2021 French rounds recorded about 100 times above comparable rounds by the same investor are set to zero.



a) EU27 targets b) US targets

Figure B.15: Investor source shares over time, 2000–2024, all PE/VC stages

Notes: LSEG financing rounds, 2000–2024. All investment stages and all investor types are included. Recording errors in LSEG amounts are corrected: the 2020 Danggeun Market round, recorded at $40.3bn, is set to its reported $33m. A batch of 2019–2020 French rounds recorded about 1000 times too large is divided by 1000. The amounts of two 2021 French rounds recorded about 100 times above comparable rounds by the same investor are set to zero.

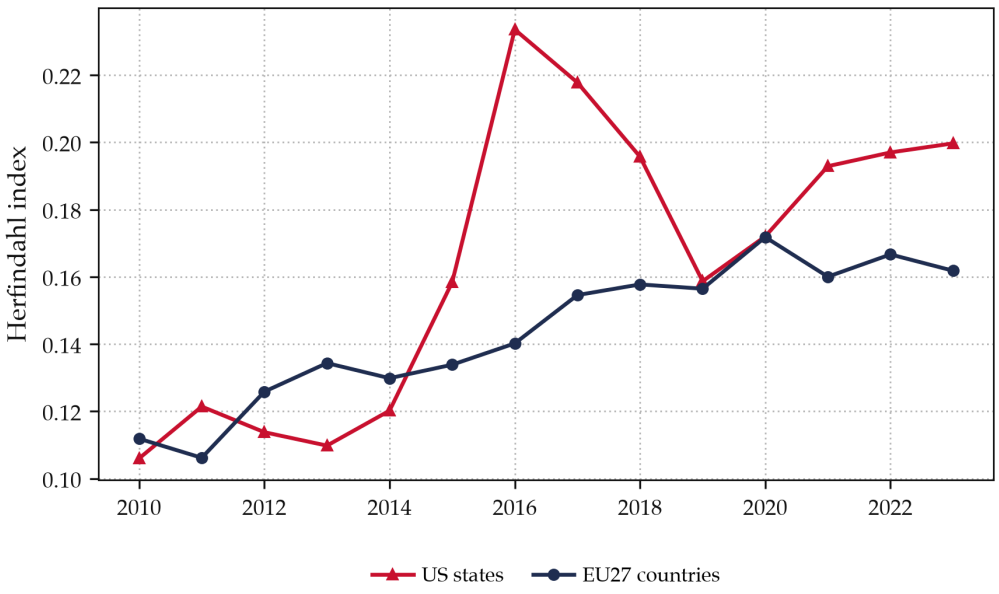


Figure B.16: Concentration over time, all PE types: Herfindahl index across locations

Notes: LSEG financing rounds, all investment stages and investor types. Each point uses the three-year window ending in that year, 2010–2023. Higher values indicate more spatial concentration of investment received across states (US) or countries (EU27). Amounts are positive investor-specific amounts, with the corrections in Appendix B.1.

B.5 EU passports for venture capital funds

A regulatory passport sets common rules, so that a product authorized in one member state can be offered in all of them. The EU first used this approach for mutual funds in 1985. It extended the idea to issuers of public securities in 2003, but private issues are exempt and did not receive a passport. Ewens and Farre-Mensa (2020) review this regulatory environment.

Two regimes now give venture capital managers a passport. The Alternative Investment Fund Managers Directive (2011/61/EU) lets an authorized manager market funds to professional investors across the EU without separate authorization in each member state. Authorized managers must meet disclosure, reporting, capital and depositary requirements. For managers of closed-ended, unleveraged funds, the Directive applies from EUR 500 million of assets.

The European Venture Capital Funds Regulation (345/2013, EuVECA) is a voluntary regime with lighter requirements for smaller managers. A registered manager can market a fund across the EU to professional investors and to other investors who commit at least EUR 100,000. The fund must intend to invest at least 70% of its capital in qualifying investments, which are mainly equity in unlisted firms. Regulation 2017/1991 widened the regime from March 2018. It raised the limit for eligible firms from 249 to 499 employees, added small firms listed on SME growth markets, opened the label to managers fully authorized under the Directive, which include larger ones, and prohibited host-country fees. Regulation 2019/1156 added common rules on pre-marketing, which apply from August 2021.

Both passports concern a fund's marketing to its own investors. EuVECA does not address other barriers, such as tax legislation, and its uptake has been small: the European Securities and Markets Authority's register listed only 27 EuVECA funds in August 2019 (Ewens and Farre-Mensa, 2020). In January 2026 the European Commission opened a consultation on the barriers that venture and growth capital managers face under EuVECA, the Directive and national fund rules.

C Bilateral frictions: additional results

These tables complement Section 4. They report the pooled gravity estimates, tests of equal coefficients across pair types, estimates with other bilateral variables, a comparison of estimated and inverted round trips, and estimates by five-year window.

Variables. VC flows are disclosed investor-specific LSEG amounts, as in Appendix B.1. Distance d_{in} is the population-weighted average of the great-circle distances between the cities of two locations, in kilometers. It follows Mayer and Zignago (2011) and Pellegrino,

Spolaore and Wacziarg (2025), and uses GeoNames city populations. Internal distance d_{ii} applies the same formula to the cities within a location. A common border is a dummy for two locations that share a land border. For countries it comes from Pellegrino, Spolaore and Wacziarg (2025), and for US states I code it from the map of state borders. Common legal origin is a dummy for two countries with the same legal origin in the classification of La Porta, Lopez-de Silanes and Shleifer (2008). Cultural distance comes from Pellegrino, Spolaore and Wacziarg (2025), who build it from answers to the World Values Survey and European Values Survey on values and beliefs. I use its 1998 wave, which predates the sample, and standardize it over the pairs of EU countries. The notes to Table C.2 define the other bilateral variables.

Further results from the pooled estimates. I cannot reject that the EU distance coefficient equals the coefficient for other pairs (both -0.41, $p = 0.98$). A common border does not raise investment between US states (0.02, not significant), and the difference with the EU coefficient is significant ($p < 0.001$). In Table 2 a location's fixed effects are estimated from EU partners alone, while here they use all partners, and 71% of the cross-border VC received by EU locations comes from outside the EU. With separate fixed effects for EU and non-EU partners, the EU distance coefficient is -0.96 (0.18), close to Table 2, and the EU border coefficient falls to 0.28 (not significant). The US distance coefficient is -0.12 and common legal origin falls to 0.38. The EU distance coefficient is larger in absolute value than the US one in every specification.

Figure C.1 plots the home effects η_i of equation (30). The European mean is 5.00 and the US mean 3.87, which correspond to h_i of 1.73 and 1.52. Greece, Romania and Bulgaria have the largest home effects in Europe, and West Virginia and South Dakota in the US. The home effect is close to zero or negative for Cyprus, Luxembourg, Delaware and Rhode Island, where many investors are holding entities registered there.

Comparison with τ inverted from the data. The model also gives the round trip directly from observed flows, using the same ratio of flows as Novy (2013):

$$\sqrt{\tau_{in}\tau_{ni}} = \left[\frac{\widetilde{Q}_{ii}\,\widetilde{Q}_{nn}}{\widetilde{Q}_{in}\,\widetilde{Q}_{ni}}\right]^{\frac{1}{2\epsilon}}, \tag{C.1}$$

where $\widetilde{Q}_{in}$ is the 2000–2019 total. This requires no model object, but it is defined only where all four flows are positive, which holds for 869 of the 2,775 pairs and 98% of VC dollars. Table C.3 compares it with the estimated round trip on those pairs. Weighted by flows, the two are within about 1% for pairs between EU countries, between US states, and between EU countries and US states. Without weights, they are within 2% between EU countries and between US states, while between EU countries and US states the estimate

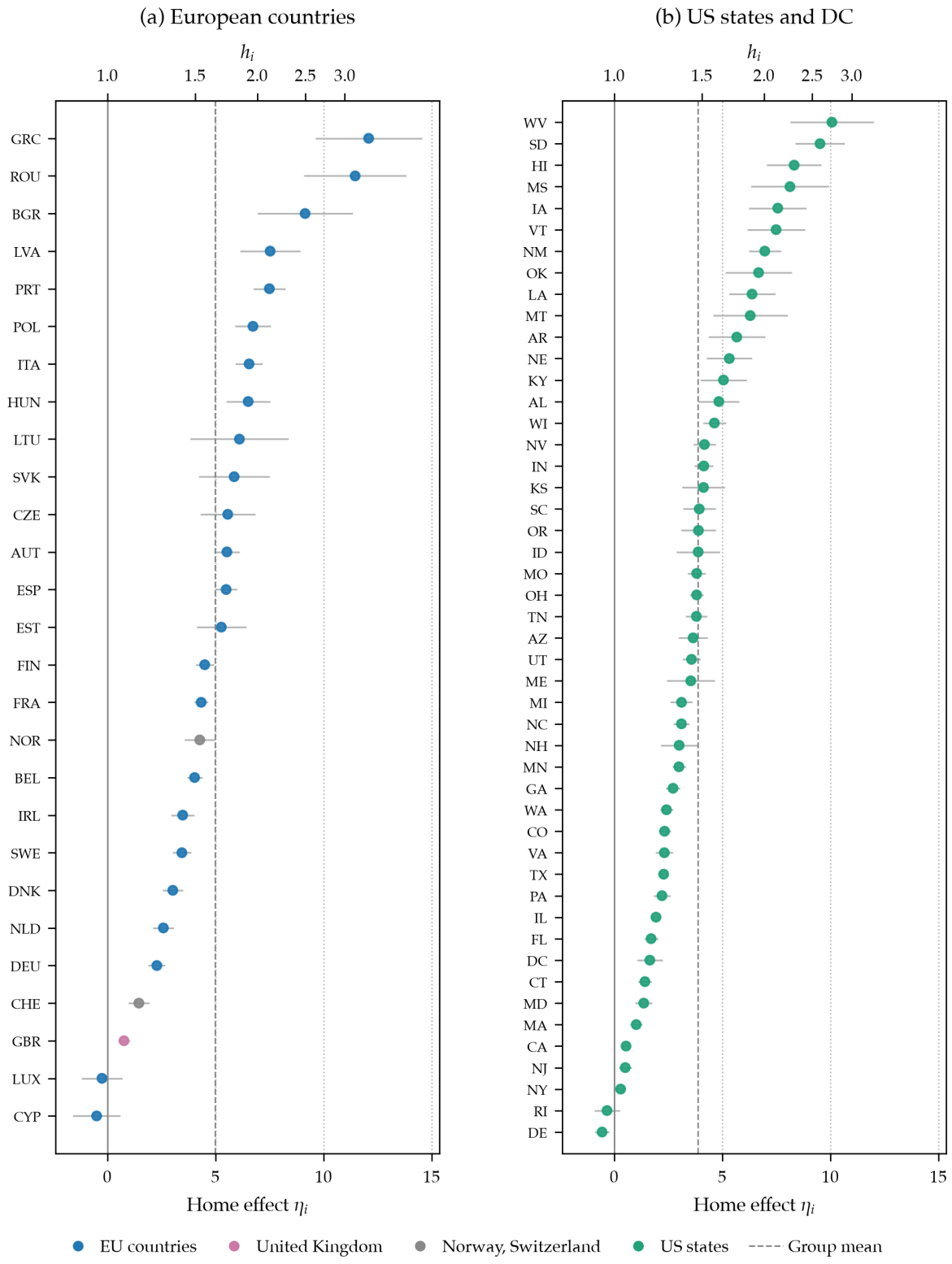


Figure C.1: Home effects by origin

Notes: Origin home effects $\eta_i = \epsilon \ln h_i$ from equation (30), Table 3, 2000–2019. The bottom axis is in log investment and the top axis shows h_i with $\epsilon = 10$. Bars are 95% confidence intervals with standard errors clustered by directed pair. Dashed lines are group means. The left panel includes the UK, Norway and Switzerland. Croatia, Malta, Slovenia, Alaska, North Dakota and Wyoming are not identified.

is 1.54 against 1.60 in the data, so the observable variables understate the frictions on thin transatlantic pairs. The log correlation across all pairs is 0.71. The estimated τ uses the same flows, so this is a check on its functional form and not an out-of-sample test. I use the estimated τ in the model because it is defined for every pair, including the pairs with zero flows, where equation (C.1) is not, and because its components can be changed in the counterfactuals.

Other bilateral variables and stability. I add to equation (30) other bilateral variables that can explain the frictions, one at a time and then together: common currency, insolvency distance, capital gains tax distance, equity tax retention, bilateral trust, working-hours overlap, migration, technological distance, direct flights and linguistic distance. Added alone, four are significant at the 5% level for EU pairs (Table C.2): capital gains tax distance, working-hours overlap, direct flights and linguistic distance. Added together, only capital gains tax distance (-0.63) and migration (-0.14) remain significant for EU pairs. The EU distance coefficient moves little, from -0.41 to -0.38, while the US coefficient falls from -0.15 to -0.04 and is no longer significant, so the EU-US gap widens. The coefficient for other pairs falls to -0.17. Common legal origin (0.87) and the EU border (0.66) remain significant, and cultural distance remains insignificant. The round trip falls to 1.69 between EU countries and barely moves for the other pair types. I keep these variables out of τ. The EU-US gap in home effects is less robust than the gap in distance coefficients. The mean of η_i is 5.35 for EU countries and 3.87 for US states in the baseline, 3.22 and 3.90 with separate fixed effects for EU and non-EU partners, and 4.20 and 5.02 with all ten variables.

I also estimate equation (30) separately on five-year windows from 2000 to 2024 (Table C.4). The EU distance coefficient is larger in absolute value than the US one in every window, and the round trip between EU countries and US states is above those within the EU and within the US in every window. Common legal origin falls from 1.31 in 2000–04 to 0.65 in 2020–24, and remains significant throughout. Cultural distance is significant only in 2020–24, which is consistent with its insignificance over 2000–2019. The windows extend to 2024 to show this change.

Table C.1: Tests of equal coefficients across pair types

Variable	Hypothesis	χ^2 [p-value]
Log distance	EU–EU = US–US	10.90 [< 0.001]
Log distance	EU–EU = other	0.00 [0.983]
Log distance	US–US = other	88.81 [< 0.001]
Common border	EU–EU = US–US	12.34 [< 0.001]
Common border	EU–EU = other	1.59 [0.208]
Common border	US–US = other	2.29 [0.130]

Notes: Wald tests of equal coefficients across pair types for column (4) of Table 3. Each row tests one restriction (χ^2 with one degree of freedom), with p-values in brackets. The other type pools transatlantic, UK and Norway/Switzerland pairs, so these tests do not compare the EU with the transatlantic slope alone. Standard errors clustered by directed pair.

Table C.2: Estimating τ with other bilateral variables

	(1) Baseline	(2) Added alone	(3) All ten
Log relative distance, EU–EU	-0.412^{***}		-0.379^{***}
	(0.081)		(0.134)
Log relative distance, US–US	-0.145^{***}		-0.042
	(0.036)		(0.053)
Log relative distance, other pairs	-0.414^{***}		-0.168^{**}
	(0.024)		(0.074)
Common legal origin, EU–EU	0.984^{***}		0.869^{***}
	(0.123)		(0.153)
Cultural distance (std.), EU–EU	-0.115		-0.104
	(0.093)		(0.108)
Common border, EU–EU	0.595^{***}		0.656^{***}
	(0.128)		(0.192)
Common border, US–US	0.019		0.039
	(0.106)		(0.109)
Common border, other pairs	0.343^{*}		0.315
	(0.189)		(0.194)
Common currency, EU–EU		0.028	0.148
		(0.163)	(0.199)
Insolvency distance, EU–EU		0.094	0.261
		(0.340)	(0.399)
Capital gains tax distance, EU–EU		-0.443^{**}	-0.629^{***}
		(0.225)	(0.241)
Equity tax retention, EU–EU		-0.232	0.869
		(0.665)	(1.069)
Bilateral trust, EU–EU		0.219	-0.402
		(0.554)	(0.781)
Working-hours overlap, EU–EU		0.144^{***}	0.159
		(0.039)	(0.151)
Log migration (lagged), EU–EU		0.002	-0.142^{**}
		(0.025)	(0.063)
Technological distance, EU–EU		0.010	-0.506
		(0.687)	(0.707)
Log flights (lagged), EU–EU		0.119^{***}	0.041
		(0.042)	(0.048)
Linguistic distance, EU–EU		-2.621^{***}	-1.294
		(0.842)	(1.134)
Locations	81	81	81
Observations	98,991	98,991	98,991
Origin home effects	Yes	Yes	Yes
Origin × year FE	Yes	Yes	Yes
Destination × year FE	Yes	Yes	Yes

Notes: PPML estimates of equation (30), same sample as Table 3. Column (1) is the baseline. Column (2) adds each variable in a separate regression, and column (3) adds all ten. Only EU–EU slopes of the added variables are shown. Regressions also include slopes for other pair types where a variable varies. Insolvency and linguistic distance have slopes for other pairs. Capital gains tax distance, working-hours overlap, technological distance and flights have slopes for US and other pairs. Migration has a slope for US pairs. Common currency, equity tax retention and bilateral trust enter for EU pairs only. All added variables are zero on domestic pairs, and missing cells are set to zero with a missing indicator by pair type (not shown), so every regression keeps the same observations. Common currency: both countries use the euro in year t. Insolvency distance: OECD insolvency-regime distance (2010, 2016 and 2022 waves). Capital gains tax distance: absolute gap in log one-year capital gains retention rates. Equity tax retention: Pellegrino, Spolaore and Wacziarg (2025) directed statutory retention on equity income, one cross-section. Bilateral trust: Eichengreen and Saka (2025), one cross-section. Working-hours overlap: $\max(0, 8 - |\Delta\text{UTC}|)$. Log migration: Eurostat bilateral migration summed over $t-1$ to $t-3$. Technological distance: cosine distance between PATSTAT IPC3 patent profiles over the previous five years. Log flights: direct departures in $t-1$. Standard errors clustered by directed pair in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.3: Estimated and inverted round trips

		Unweighted		Flow-weighted		
Pair type	Pairs inverted	Estimated	Inverted	Estimated	Inverted	Log corr.
EU–EU	81 of 276	1.535	1.507	1.355	1.344	0.69
US–US	525 of 1,128	1.366	1.349	1.165	1.165	0.61
EU–US	163 of 1,152	1.543	1.596	1.406	1.402	0.70
All pairs	869 of 2,775	1.420	1.418	1.204	1.202	0.71

Notes: Geometric means of the round trip $\sqrt{\tau_{in}\tau_{ni}}$ on pairs where equation (C.1) is defined, disclosed VC amounts, 2000–2019, $\epsilon = 10$. Estimated: from Table 3, column (4). Inverted: equation (C.1). Flow weights: $\widetilde{Q}_{in} + \widetilde{Q}_{ni}$. All pairs also include UK, Norway and Switzerland pairs. Log corr.: correlation of the log estimated and log inverted round trips across pairs. The estimated round trip uses the same flows, so this comparison is partly targeted.

Table C.4: Estimating τ by five-year window

	2000–04	2005–09	2010–14	2015–19	2020–24
Log relative distance, EU–EU	-0.433^{***}	-0.554^{***}	-0.376^{**}	-0.369^{***}	-0.204^{***}
	(0.146)	(0.148)	(0.175)	(0.080)	(0.064)
Log relative distance, US–US	-0.156^{***}	-0.212^{***}	-0.211^{***}	-0.085	-0.049
	(0.039)	(0.048)	(0.038)	(0.055)	(0.036)
Log relative distance, other pairs	-0.416^{***}	-0.486^{***}	-0.488^{***}	-0.355^{***}	-0.358^{***}
	(0.039)	(0.040)	(0.031)	(0.033)	(0.021)
Common legal origin, EU–EU	1.312^{***}	1.157^{***}	0.779^{***}	0.862^{***}	0.654^{***}
	(0.208)	(0.179)	(0.248)	(0.146)	(0.104)
Cultural distance (std.), EU–EU	-0.075	-0.185	0.079	-0.163	-0.467^{***}
	(0.180)	(0.141)	(0.193)	(0.120)	(0.091)
Common border, EU–EU	0.183	0.350^{*}	0.496^{**}	0.867^{***}	0.235^{**}
	(0.217)	(0.195)	(0.233)	(0.156)	(0.105)
Common border, US–US	0.054	0.102	-0.056	-0.032	0.197^{**}
	(0.106)	(0.126)	(0.136)	(0.137)	(0.099)
Common border, other pairs	0.604^{**}	0.412	0.013	0.372	0.447^{**}
	(0.284)	(0.279)	(0.247)	(0.231)	(0.215)

Notes: PPML estimates of equation (30) on each window separately, with new fixed effects and home effects in each. Cultural distance keeps its 2000–2024 standardization. Locations with no domestic flows in a window have no home effect in that window. Standard errors clustered by directed pair in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

D Quantitative analysis: data and model fit

This section documents the inputs and validation series used in Section 5, reports the model fit, and repeats the experiments of Section 6 with a destination payoff. Unless stated otherwise, the quantitative sample consists of 16 EU countries, the UK and 45 US states, and levels are annual means over 2000–2019. Within-sample VC flows exclude origins and destinations outside these 62 locations. The bilateral-friction estimation instead uses the larger geographic sample described in Section 4, over the same 2000–2019 window.

D.1 Model sample

Of the 78 locations in the EU27, the UK and the 50 US states, the model leaves out Bulgaria, Croatia, Cyprus, Greece, Latvia, Lithuania, Luxembourg, Malta, Romania, Slovakia, Slovenia, Alaska, Hawaii, North Dakota, South Dakota and Wyoming. Cyprus and Luxembourg are holding-company domiciles: over 2000–2019 their investors place $2.4 billion and $2.8 billion in VC in the 78 locations, against 3 and 9 patent families. Wyoming has no domestic VC in 2000–2019. Eleven other locations have almost no VC-backed patents. Latvia and Hawaii are left out for a different reason. With output per worker measured at purchasing power parity, adoption is faster and returns to VC are lower, and the model cannot reproduce the VC that these two locations supply at any participation cost. Their cost would be zero, and with a zero cost their VC supply has no limit in the experiments. They hold 0.04% of VC-backed patents and 0.06% of the VC flows in the 64-location matrix. Together the 16 locations left out have 0.09% of VC-backed patents, and flows that start or end in one of them are 1.3% of the disclosed VC among the 78 locations.

Over 2000–2019, the 16 EU countries account for 97% of the disclosed VC received by startups in the EU27 and 91% of the disclosed VC invested by EU27 investors. The 45 US states account for nearly all of the US totals. Table D.1 gives shares by block.

D.2 Data sources

VC investment and innovation. VC amounts come from LSEG investor-specific investment records, with the stage restrictions, investor exclusions and amount corrections documented in Appendix B.1. These are monetary flows, not funding-round counts or investor-round counts. The targets use VC supplied by each origin within the model sample. VC-backed patent families are constructed from the LSEG–PATSTAT match described in Appendix B.3. PATSTAT citation links also provide the geographic citation home-bias measure used to construct adoption probabilities in Section 5.2. The mapping from citation home bias to adoption is an assumption of the model. Its two parameters

Table D.1: Model sample, shares by block, 2000–2019 (percent)

	Locations	Patents	VC received	VC invested	GDP	Employment
EU	16	14.1	11.3	10.7	41.8	49.5
United Kingdom	1	4.6	6.0	7.8	8.5	8.6
United States	45	81.3	82.7	81.6	49.7	41.9
Sample total	62	7,085	$40.7bn	$40.7bn	$30.0tn	346m

Notes: Annual means over 2000–2019. The first column is a count, and the last row gives sample totals per year. Patents: patent families of VC-backed firms, defined in Appendix B.3. VC: disclosed amounts in Seed, Early, Expansion and Later stage rounds between the 62 locations, excluding Government Affiliated and University Program investors. GDP: current US dollars, from the World Bank for countries, and for US states from BEA real state GDP times the national ratio of nominal to real GDP in each year. Employment: 2015–2019 level times each location's ratio of mean employment in 2000–2019 to 2015–2019. Levels come from Eurostat for EU countries, the Penn World Table for the UK, and the QCEW for US states, rescaled so the US total equals Penn World Table employment. Ratios come from the Penn World Table for European countries and Census BDS for US states.

are estimated in Section 5.2, but no observed adoption rates enter the estimation.

Employment. European employment reference levels are 2015–2019 averages from Eurostat national accounts, dataset `nama_10_pe`, item `EMP_DC`, the domestic employment concept, converted from thousands of persons to persons. The UK reference level is Penn World Table (PWT) 11.0 employment, variable `emp`, converted from millions to persons. US state reference levels are annual average employment from the Bureau of Labor Statistics Quarterly Census of Employment and Wages (QCEW), all ownerships and industries. QCEW state levels are multiplied by the common factor 1.10699 so that employment across all 50 states in 2015–2019 sums to PWT US employment. This adjusts the national total to include employment outside QCEW coverage but retains the QCEW state distribution.

Each reference level is multiplied by the location's ratio of mean employment in 2000–2019 to mean employment in 2015–2019. These ratios use PWT `emp` for European countries and employer employment from the US Census Bureau's Business Dynamics Statistics (BDS) for states. Thus state employment combines a QCEW geographic distribution, a PWT national scaling factor and BDS time variation. It is not a directly observed harmonized employment panel. The model's L_i divides the resulting levels by their arithmetic mean across the 62 locations. No hours-worked adjustment is made.

GDP and output per worker. Country GDP is the World Bank's GDP in current US dollars, indicator `NY.GDP.MKTP.CD`. US state GDP in the calibration is constructed from BEA real state GDP, table `SAGDP9`, multiplied in each year by the US national nominal-to-real GDP ratio. This is an approximation to nominal state GDP, not a state-specific deflator. GDP per worker divides the 2000–2019 mean GDP level by the

constructed employment level described above. It is neither GDP per capita nor GDP per hour. GDP in current dollars supplies the denominator of the VC outflow target. The VC targets stay in current dollars: each is VC relative to the same location's GDP, so converting both to purchasing power parity would leave it unchanged. For productivity comparisons I convert GDP to purchasing power parity. For countries I divide GDP in current dollars by the Penn World Table 11.0 price level of output (`pl_gdpo`, USA = 1) in each year and average over 2000–2019. For US states I divide by the BEA regional price parity for all items (`SARPP`, US = 100), averaged over 2008–2019, the years for which it exists, and hold relative prices at that average for 2000–2007. Regional price parities measure consumer prices rather than output prices. Most of the reduction in the spread comes from countries: with PPP for countries alone the standard deviation of log GDP per worker falls from 0.35 to 0.20 on 64 locations, and adding state prices lowers it to 0.19. The standard deviation of log GDP per worker at PPP across the 62 locations, 0.17, is one of the two statistics behind ν_b and $\bar{b}$, while its pattern across locations is an untargeted diagnostic. This calibration series differs from the direct BEA current-price GDP series used in some descriptive figures.

TFP. The TFP regression behind ν_b and the productivity diagnostic use PWT 11.0, variable `ctfp`, averaged over 2000–2019. It is the comparative TFP level at current purchasing power parities, normalized to the US, rather than the within-country time-series index `rtfpna`. The TFP regression uses 29 European countries, the EU countries except Croatia, the UK, Norway and Switzerland, and the fit comparison uses the 16 EU countries of the model and the UK. There are no observations for US states. Model a_i and observed TFP are separately geometric-mean normalized over these 17 countries for the figure. Their log correlation measures association without equating technology relative to the frontier with the measured TFP residual.

Business R&D. The independent research-intensity comparison uses business enterprise R&D expenditure (BERD) over 2015–2019. European BERD comes from Eurostat `rd_e_berdindr2`, with current-price GDP from `nama_10_gdp`, both in millions of euros. US state BERD comes from the National Center for Science and Engineering Statistics (NCSES), BRDIS/BRDS/BERD table 13, business R&D performed in current dollars. The state GDP denominator comes from BEA `SAGDP1` in current dollars. Each ratio is the sum of BERD divided by the sum of GDP over common available years within 2015–2019. The UK has no usable ratio in these extracted files, leaving 61 of the 62 locations. This is total business research, not exclusively research by VC-backed firms. Its geographic pattern can be compared with model VC-funded research intensity, but the two levels and windows differ.

Pension assets and household portfolios. These series enter only the comparison with φ_i in Section 5.4. Funded pension assets over GDP come from the OECD Pension Markets in Focus database, averaged over 2000–2019 for the 16 EU countries. The share of market assets in household portfolios comes from Eurostat household financial accounts for EU countries and from the Survey of Income and Program Participation for US states, over 2009–2019. The two household measures are defined differently, so I demean their logs by year within each bloc and compare them only within a bloc.

D.3 Calibration of adoption

This section describes how I set the two parameters of equation (33) in Section 5.2. Citations are the standard measure of knowledge flows between locations (Jaffe, Trajtenberg and Henderson, 1993; Jaffe and Trajtenberg, 2002), and they have been used to measure how ideas diffuse across countries (Eaton and Kortum, 1996; Peri, 2005; Cai, Li and Santacreu, 2022). Knowledge flows are strongly localized: patents cite patents from the same location more than a control group would predict (Jaffe, Trajtenberg and Henderson, 1993; Thompson and Fox-Kean, 2005), and the same holds across national borders (Peri, 2005). The odds in h_i^c account for differences in the relative availability of domestic and foreign patents: a large location cites itself more often simply because it produces more patents. The assumption that locations with lower citation home bias adopt frontier technologies more readily is in the spirit of models where the speed of technology diffusion differs across countries (Comin and Hobijn, 2010; Buera and Oberfield, 2020).

I estimate the two parameters jointly by indirect inference (Gouriéroux, Monfort and Renault, 1993; Smith, 1993): I choose them so that two statistics computed on model output equal the same statistics computed on the data. The first statistic comes from the citation data. I regress log TFP from the Penn World Table (Feenstra, Inklaar and Timmer, 2015), averaged over 2000–2019, on $\log h_i^c$ and $\log \eta_i$ across 29 European countries: the EU countries except Croatia, which has no VC-backed patents, the United Kingdom, Norway and Switzerland. The regression follows the literature that relates productivity to knowledge flows from abroad (Coe and Helpman, 1995; Keller, 2002). Countries with more citation home bias have lower TFP given their innovation: the coefficient on $\log h_i^c$ is -0.049 (robust s.e. 0.044). On the balanced growth path, $a_i = (\kappa\eta_i + b_i)/(g - 1 + \eta_i + b_i)$. Measured TFP in the model is $a_i^{1-\alpha}$, as in Section 5.3, so in the model I run the same regression on $(1-\alpha)\log a_i$. Desmet, Nagy and Rossi-Hansberg (2018) follow the same approach for trade costs: they run a gravity regression on data simulated by their model and choose the parameter that matches the distance elasticity in the data.

The regression includes countries that are not among the 62 locations of the model. This is possible because a_i depends only on a country's own patents and citations, and

not on the rest of the equilibrium. For these countries I compute η_i from their VC-backed patents on the same scale as the model locations, and b_i from equation (33) with the mean of $\log h_j^c$ over the 62 model locations.

The second statistic is the standard deviation of log GDP per worker across the 62 locations, which I compare with the standard deviation of $\log a_i$. I measure GDP at purchasing power parity, because the model has a single final good and no differences in prices across locations. At purchasing power parity the standard deviation is 0.17, against 0.32 at market exchange rates, because the poorer EU countries also have lower prices. Appendix D.2 describes the conversion.

Since η_i is set by patent shares, a_i depends only on b_i, so both statistics can be computed without solving the rest of the model. The estimates are $\nu_b = 0.116$ (s.e. 0.133) and $\bar{b} = 0.011$. The standard error maps the robust standard error of the TFP coefficient into ν_b, holding the second statistic at its data value. The estimate is imprecise: the 95% confidence interval runs from -0.14 to 0.38 and includes zero. It is also sensitive to single countries: dropping Latvia lowers it to 0.01, and dropping Norway or Romania raises it to 0.19 or 0.18. On the 17 European countries of the model it is 0.30 (s.e. 0.35).

For these reasons I do not use the point estimate. I set $\nu_b = 0.05$, which lies inside the confidence interval, and $\bar{b} = 0.0088$, which matches the spread of output per worker at that value. The baseline therefore matches the second statistic exactly but not the first: at $\nu_b = 0.05$ the model coefficient on $\log h_i^c$ is smaller in absolute value than in the data. Appendix D.6 reports the results with homogeneous adoption and with $\nu_b = 0.15$, which is above the point estimate.

The two statistics play different roles. The citations determine which locations adopt more, and the dispersion of output per worker determines the level of adoption. A lower $\bar{b}$ leaves locations with few VC-backed patents far behind the frontier and makes productivity too dispersed. A higher $\bar{b}$ brings every location close to the frontier. I read b_i as a reduced-form probability that a product line adopts the frontier technology. Its average across product lines sets how fast a location catches up with the frontier, and it is not observed directly in the data. The catch-up rate is low because it must reconcile two facts: locations with few VC-backed patents are not much poorer than others at purchasing power parity, and adoption cannot be so fast that every location sits at the frontier. Adoption probabilities range from 0.0077 to 0.0092 across EU countries and from 0.0081 to 0.0098 across US states.

D.4 A microfoundation for adoption

I use a Fréchet model to connect where entrepreneurs look for ideas to where patents cite, following Eaton and Kortum (2002) and Buera and Oberfield (2020). This lets me measure access to knowledge with citations. I then assume that access to better ideas

raises the probability of adopting the frontier, which leads to an equation of the same form as equation (33). The law of motion for productivity does not change.

Each entrepreneur l in location i looks for an existing technology to build on. For each location n, the entrepreneur draws a match quality $\xi_{in}(l)$ from a Fréchet distribution with shape $\theta > 1$ and scale one, independently across locations. The value of learning from n is

$$\frac{\Omega_n \, \xi_{in}(l)}{d_{in}}, \tag{D.1}$$

where Ω_n is the stock of knowledge in location n and $d_{in} \geq 1$ is a bilateral diffusion friction, with $d_{ii} = 1$. The entrepreneur learns from the best source and cites it. The share of entrepreneurs in i whose best source is in n is

$$z_{in}^c = \frac{(\Omega_n / d_{in})^\theta}{\Psi_i}, \qquad \Psi_i \equiv \sum_{m=1}^{N} \left(\frac{\Omega_m}{d_{im}} \right)^\theta. \tag{D.2}$$

The term Ψ_i measures how well location i is connected to knowledge produced around the world. These shares have the form of the trade shares in Eaton and Kortum (2002, eq. 8), with sources of knowledge in place of suppliers of goods, and the quality of the best source in i, Q_i, is again Fréchet with shape θ and scale Ψ_i. I observe citations made by patents, not the sources used by entrepreneurs who adopt. I therefore assume that the citations of patenting firms in a location reveal the same sources that its adopters draw on.

I assume that better access to knowledge makes adoption more likely, and that the probability of adopting the frontier is proportional to a power of the quality of the best source:

$$b_i = c \, \mathbb{E}\left[Q_i^{\theta \nu_\Psi} \right] = c \, \Gamma\left(1 - \nu_\Psi\right) \Psi_i^{\nu_\Psi}, \qquad 0 \leq \nu_\Psi < 1, \tag{D.3}$$

where $c > 0$ is a constant. The expectation follows from the Fréchet distribution, as in footnote 18 of Eaton and Kortum (2002), and it is finite only when $\nu_\Psi < 1$. The exponent ν_Ψ is the elasticity of adoption with respect to access to knowledge. The case $\nu_\Psi = 1/\theta$ makes adoption proportional to the expected quality of the best source. A moment of the same form drives the growth of knowledge in equation (4) of Buera and Oberfield (2020), but there it governs how new ideas build on existing ones. Its use for the adoption of the frontier is my assumption. The constant c must keep b_i below one, which holds easily since adoption probabilities in the calibration are close to 0.01. Normalizing by the geometric mean gives

$$b_i = \bar{b} \exp\left[\nu_\Psi \left(\log \Psi_i - \frac{1}{N} \sum_{j=1}^{N} \log \Psi_j \right) \right], \tag{D.4}$$

where $\bar{b}$ is again the geometric mean of adoption probabilities. Given equation (D.3), the

Fréchet distribution delivers this power form in Ψ_i.

The access term Ψ_i is not observed, but citations reveal it. If diffusion frictions are symmetric, $d_{in} = d_{ni}$, equation (D.2) implies for every pair of locations

$$\log \Psi_i - \log \Psi_n = \frac{1}{2} \log \left(\frac{z^c_{ni}\, z^c_{nn}}{z^c_{in}\, z^c_{ii}} \right). \tag{D.5}$$

This applies the normalized share in equation (12) of Eaton and Kortum (2002) to both directions of a pair, so that the knowledge stocks Ω_n and the symmetric frictions cancel. I measure z^c_{in} with the PATSTAT citation network. Let C_{in} be the number of citations from patent families with inventors in i to patent families with inventors in n. A family groups the applications for the same invention across patent offices, and I use the citations between families, which pool all offices. Both families have their earliest filing in 2000–2019, and the cited family was filed in an earlier year than the citing one. I use all patents, not only those of VC-backed firms. I assign families to locations by inventor address, using the state for US inventors, and split each family equally across its located inventors, so each citation has a total weight of one. Citations between families of the same applicant are kept, and I do not separate citations added by applicants from those added by examiners. The citation share is

$$z^c_{in} = \frac{C_{in}}{\sum_{m=1}^{N} C_{im}},$$

with the sum over the 62 locations. Every cell of the citation matrix is positive, so no cell needs to be filled in before taking logs. The 62 locations give 1,891 pairs, and each pair gives one estimate of a difference in $\log \Psi$. I recover $\log \Psi_i$ up to a constant by weighted least squares, regressing the right-hand side of equation (D.5) on the difference of the two location indicators. The weights rise with the number of citations behind the four shares of each pair.

Symmetric frictions are a restriction the data can reject, and I check it in three ways. First, $d_{in} \geq 1$ requires $z^c_{ii} z^c_{nn} \geq z^c_{in} z^c_{ni}$. This holds for all 1,891 pairs, but it is a weak test, because locations cite themselves much more than they cite others. Second, one index per location fits the pairwise differences closely, with a weighted R^2 of 0.986. Third, symmetry implies that for any three locations

$$z^c_{ni}\, z^c_{mn}\, z^c_{im} = z^c_{in}\, z^c_{nm}\, z^c_{mi}. \tag{D.6}$$

Across the 37,820 triples, the median absolute gap between the logs of the two sides is 0.21. It is 0.15 in the 9,874 triples where every cell has at least 1,000 citations. The gaps are not zero, so I treat symmetric Fréchet sourcing as a close approximation to the citation data.

The recovered index is almost the same as the citation home bias in equation (33). Across the 62 locations of the model, $\log \Psi_i$ and $\log h_i^c$ have a correlation of -0.99, and a regression of the first on the second has a slope of -0.51. Part of this link is mechanical, since both measures are built from the same own-citation shares z_{ii}^c, so I do not read it as separate evidence for the model. It does mean that using Ψ_i in place of h_i^c would give almost the same adoption probabilities. Substituting into equation (D.4) gives equation (33) with

$$\nu_b \simeq 0.51\, \nu_\Psi. \tag{D.7}$$

The slope is below one in absolute value because a location with good access is also cited more by others, which raises the odds in h_i^c on both sides.

Under this assumption ν_b is bounded. Given the estimated relation between access to knowledge and citation home bias, the restriction $\nu_\Psi < 1$ implies an approximate upper bound of 0.51 for ν_b. The baseline value $\nu_b = 0.05$ corresponds to $\nu_\Psi \simeq 0.1$, which means that access to knowledge from elsewhere does little to speed up adoption. The point estimate, 0.116, corresponds to $\nu_\Psi \simeq 0.23$, and the upper end of its confidence interval, 0.38, to $\nu_\Psi \simeq 0.75$. The assumption gives no reason to expect $\nu_b < 0$, which would require entrepreneurs to adopt less when they are better connected. The microfoundation does not pin down $\bar{b}$, which still comes from the spread of output per worker. In the counterfactuals I hold Ω_n and d_{in} fixed, so b_i does not respond to changes in VC frictions.

D.5 Model fit diagnostics

I distinguish direct calibration targets, partly targeted allocation moments, and untargeted productivity comparisons. All comparisons below use the baseline of Section 5.2, without the destination payoff ψ_n and with no inversion of domestic shares.

Direct targets. The inversion of χ_i matches each location's share of VC-backed patents. The inversion of φ_i matches its VC outflow divided by its GDP. The adoption level $\bar{b}$ matches the standard deviation of log GDP per worker at purchasing power parity, and ν_b is set inside the confidence interval of the indirect inference estimate based on the TFP regression across 29 European countries, so the baseline does not match that coefficient exactly. The frontier growth rate is imposed at 2%. Employment is an input rather than a prediction. Agreement on these objects verifies the inversion, not the model's ability to explain independent outcomes. Patent shares and outflows match to numerical precision.

Partly targeted allocation moments. VC inflow shares are not targeted, but the frictions are estimated on the same flows. Their log correlation with the data is 0.95. Domestic portfolio shares are not independently informative about home bias: the estimated origin-specific home effects h_i already use domestic VC flows. They remain a

consistency check because the model replaces gravity destination effects with equilibrium returns, and uses a restricted set of locations. Consequently, the equilibrium need not reproduce domestic shares exactly. Their correlation with the data is 0.83, with a root mean squared error of 14.6 percentage points. This is not an out-of-sample test.

Output per worker. The standard deviation of log output per worker, y_i/L_i, is targeted by $\bar{b}$, but its pattern across locations is not. Its log correlation with observed GDP per worker at purchasing power parity is 0.36 across all 62 locations, 0.59 within the 16 EU countries, and 0.38 within the 45 US states. For this comparison, model and data are each divided by their unweighted geometric mean over the same 62 locations. The root mean squared log discrepancy is 0.19. Employment measures workers rather than hours, and this is not a test of output per hour. Although observed GDP enters the VC target, the cross-location pattern of output per worker is not imposed.

Technology. The equilibrium technology index a_i has a log correlation of 0.59 with Penn World Table TFP over the 16 EU countries and the UK. This comparison is partly targeted, since the TFP regression on citation home bias disciplines ν_b. It is not a match in levels: a_i measures technology relative to the model frontier and is not the national-accounts TFP residual. No state-level TFP observations enter this comparison. Since the baseline has a common capital rental rate, output per worker is proportional to a_i, so its correlation with GDP per worker does not provide a second independent productivity test.

Research intensity. Finally, model VC-funded research expenditure relative to output has a log correlation of 0.63 with observed business R&D/GDP across the 61 locations with available data. Business R&D covers more than VC-funded research and is measured over 2015–2019, rather than the calibration's 2000–2019 window. Figure D.1 therefore shows separately normalized research intensities as an untargeted comparison of their geographic pattern, without interpreting their level difference as model error. All reported correlations give equal weight to locations.

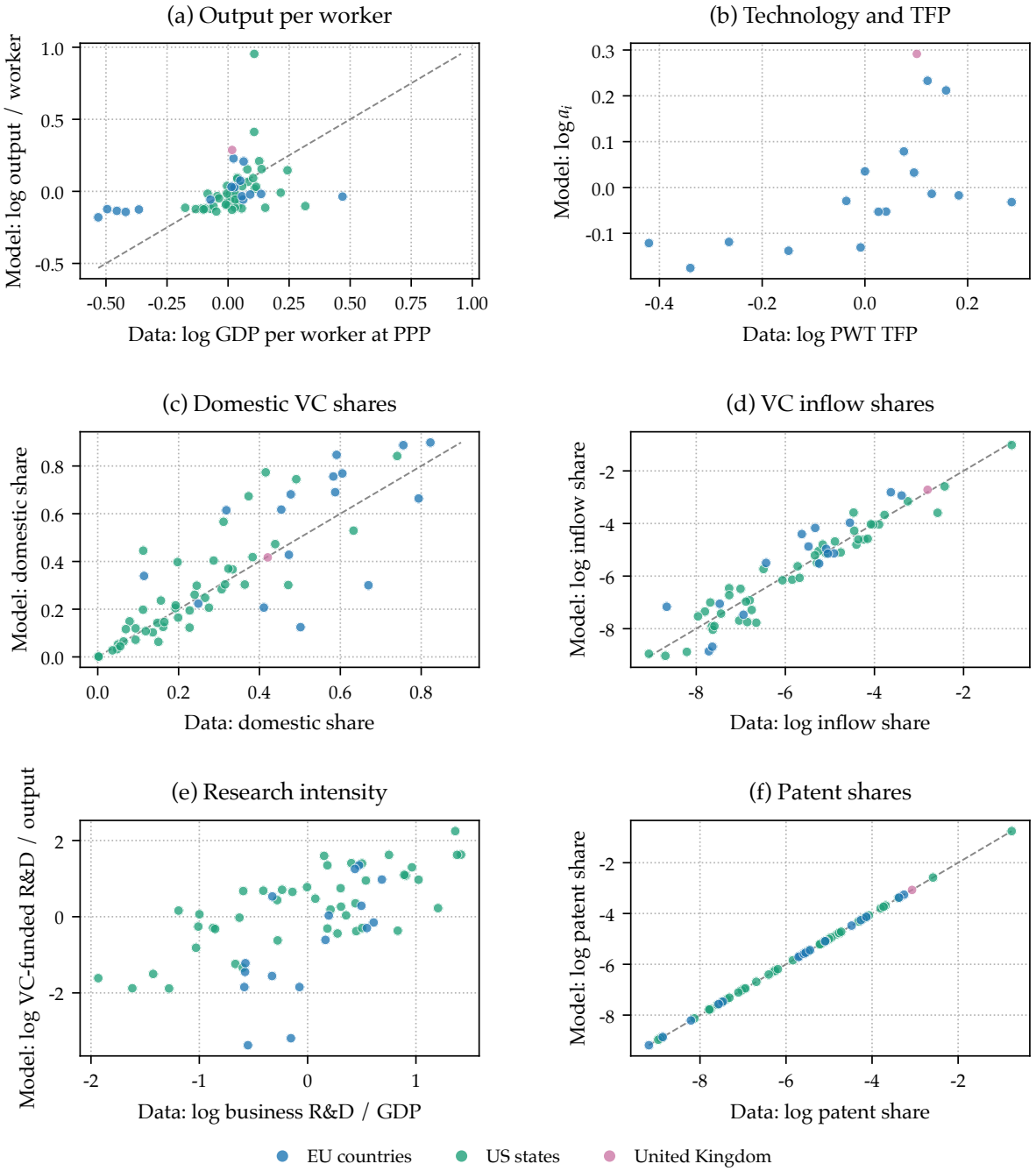


Figure D.1: Targeted and untargeted model comparisons.

Notes: The baseline, 62 locations. Output per worker in the data is at purchasing power parity. Panel a: the spread is targeted by $\bar{b}$, the pattern is not. Panel b is partly targeted, since the TFP regression disciplines ν_b. Panel e is untargeted. Panels c and d are partly targeted, and panel f is targeted. TFP is available for 17 countries and business R&D for 61 locations. Centered logs subtract the unweighted mean log on each panel's common sample, separately for model and data. Domestic shares use VC invested at home divided by all VC invested by the same origin within the sample. Inflow and patent shares use sample totals. Diagonal lines indicate equality only for comparable objects. No equality line is shown for a_i versus TFP or VC-funded research versus business R&D. Sources and measurement caveats are in Appendix D.

D.6 Robustness: adoption

Adoption shapes the productivity block, so I check how the experiments of Section 6 depend on it. Table D.2 repeats them for homogeneous adoption, $b_i = \bar{b}$, and for $\nu_b = 0.15$, which is above the point estimate of 0.116. In each case I set $\bar{b}$ to match the same spread of log output per worker. The last row repeats the experiments with GDP at market exchange rates, on the 64 locations that include Latvia and Hawaii, and with $\nu_b = 0.15$.

Table D.2: The experiments under alternative adoption calibrations

			Model	Gap closed (% of model gap)			Combined
	ν_b	$\bar{b}$	gap	Home bias	Particip. costs	Combined	(% change)
Baseline	0.05	0.0088	−0.146	3.8	6.4	19.1	2.8
Homogeneous adoption	0	0.0078	−0.148	3.9	6.7	20.0	3.0
Higher sensitivity	0.15	0.0126	−0.133	4.5	6.6	18.6	2.5
Market rates, 64 locations	0.15	0.0037	−0.274	2.2	5.9	14.3	4.0

Notes: $\bar{b}$ is set in each row so that the standard deviation of log a_i equals that of log GDP per worker, at purchasing power parity in the first three rows and at market exchange rates in the last. "Combined (% change)" is the rise in EU output per worker relative to the US under the combined policy.

The combined policy raises EU output per worker relative to the US by 2.5% to 3.0% in the three calibrations at purchasing power parity, and by 4.0% with GDP at market exchange rates. That row changes three things at once, so it is not a test of one assumption. Its share of the gap closed is lower, because the model gap is almost twice as large. At market rates the spread of output per worker is larger, so $\bar{b}$ is lower and adoption slower. Innovation then matters more for productivity, and the same reforms move productivity more. In every case the combined policy closes more than the two policies separately, so the complementarity between the two reforms does not depend on the adoption calibration.

D.7 A destination payoff

In the baseline of Section 5 the model gives EU startups too much VC and sends too little EU money abroad. Without further structure, the VC a location receives is pinned down by its innovation and the value of its patents. As a robustness check, I let a dollar of VC invested in location n pay $\psi_n \rho_n$ instead of ρ_n. I use ψ_n to absorb differences in returns that the model leaves out, such as the size of the local exit market, the quality of local fund managers, or the tax treatment of returns. It enters the portfolio shares and

VC market clearing as

$$z_{in} = \frac{(\psi_n \rho_n / \tau_{in})^{\epsilon}}{\sum_{m=1}^{N} (\psi_m \rho_m / \tau_{im})^{\epsilon}}, \qquad \psi_n \rho_n q_n = g \sum_{i=1}^{N} z_{in} R_i^v s_i^v. \tag{D.8}$$

With $\psi_n = 1$ everywhere the model is the baseline. I choose ψ_n so that each location's share of the VC received in the sample matches the data, $\sum_i \widetilde{Q}_{in} / \sum_{m,i} \widetilde{Q}_{im} = I_n / \sum_m I_m$, where $\widetilde{Q}_{in}$ is the financial flow in equation (15) and I_n is the VC received by startups in n from the 62 locations in the data. The inflow shares pin down only relative values of ψ_n. A common level would not change the shares at given returns, but it would change the return on VC relative to physical capital, and so the inverted participation costs. I set the geometric mean of ψ_n to one, and I hold ψ_n fixed in the experiments. This assumes that the policies do not change the characteristics it captures. That is reasonable for reforms of participation costs and of barriers between EU countries, but deeper integration could also improve these characteristics over time. Because ψ_n is a residual and not an estimated structural characteristic, I keep the baseline without it.

The baseline gap does not change, because a_n depends only on η_n and b_n, and the calibration holds innovation rates, adoption probabilities and frontier growth fixed. The allocation fits better: EU investors place 20% of their VC in the US, against 8% in the baseline and 22% in the data, and the correlation of domestic shares rises to 0.96. Table D.3 repeats the experiments of Section 6. Participation costs close 6.2%, close to the baseline. Removing home bias closes 7.6%, about twice as much, because some EU startups are now more attractive to investors from other EU countries. The combined policy closes 22.8% of the model gap. This is 0.033 log points: EU output per worker rises by 3.4% relative to the US.

Table D.3: Effects of the experiments with the destination payoff

	Δg	EU investors' VC going to (%)				EU VC / GDP (%)		EU innov. share	EU a (% of	Gap closed
	(pp)	Own	Other EU	US	UK	Invested	Received	(%)	US)	(%)
Data	–	58	13	22	6	–	–	–	–	–
Baseline	–	61	13	20	6	0.032	0.038	14.1	86.4	–
(1) Home bias	0.031	11	76	10	3	0.041	0.041	15.4	87.4	7.6
(2) Particip. costs	0.044	45	12	34	9	0.066	0.046	15.0	87.2	6.2
(3) Distance	0.001	58	17	19	6	0.032	0.038	14.1	86.4	0.2
(4) Combined	0.108	5	64	25	6	0.081	0.057	18.0	89.3	22.8

Notes: Same definitions as Table 5, with ψ_n inverted to VC inflow shares. The lowest EU participation cost is again Estonia's.