Industrial Policy via Venture Capital*

Martin Aragoneses†
INSEAD

Sagar Saxena‡
University of Pennsylvania

July 2, 2025

Abstract

1/3 of venture capital (VC) investment in Europe comes from the government. We study government-backed VC investment intermediated via private VC funds that focus on different stages of the firm life cycle. We link data on the portfolio of VC investments of the largest European government agency engaged in such form of industrial policy, showing large increases in the volume of VC funding per firm. Reduced-form regressions show government-linked financing via private VCs has stronger effects when focused on young firms. Despite being much less effective when targeting older firms, we find government-linked VC funds are biased towards later-stage investments in so-called "scale-ups". We develop a structural model of firm life cycle dynamics in which government spending funds entrepreneurs via private VCs. Counterfactuals show the targeting across VC stages that maximizes aggregate productivity depends on the degree of financial market imperfections. The model rationalizes the policy focus on mature firms in highly frictional markets. However, in a calibration with relatively mild financial frictions, reallocating a constant budget towards early-stages produces aggregate effects of the same magnitude as a more costly “Big Push" that increases the amount of spending.

*We gratefully acknowledge financial support from the Wharton-INSEAD Alliance. Yuancheng Li, Huaihan Shan, and Oleg Telegin provided excellent research assistance. We benefited greatly from comments from BSE, ESADE, INSEAD, NUS, EIB, and EIF. All errors are our own.

†Email: martin.aragoneses@insead.edu

‡Email: sagarsxn@wharton.upenn.edu

1 Introduction

Governments around the world use industrial policy to try to stimulate economic dynamism with mixed results.[1] Detractors argue governments end up allocating resources inefficiently because they struggle to target the "right" firms. What if industrial policy were intermediated via private funds, with the government investing passively across active funds, relying on their private expertise in selecting and supporting firms?[2]

In this paper, we investigate this form of industrial policy intermediated via Venture Capital (VC) funds which has become a common way for governments to make large-scale equity investments globally.[3] We focus on Europe because aggregate productivity and dynamism there have long been underwhelming[4]. Corporate investment in Europe significantly trails that of the United States despite substantial savings, talent, and public investment — a puzzling gap highlighted by the recent "Draghi Report" (Draghi (2024)). The VC market is one area where Europe is particularly under-capitalized compared to the US.[5] Given the importance of VC as a source of financing for innovative firms,[6] the Draghi Report and other policy analyses have called for coordinated interventions to strengthen Europe's VC ecosystem as a means to boost economic dynamism.

1/3 of new VC investment in Europe originate from government agencies.[7] Our empirical and theoretical investigation zooms into one of such agencies, the European

[1] See Juhász, Lane, and Rodrik (2024) for a survey of the literature.

[2] De Haas and González-Uribe (2024) literature review concludes empirical evidence on the effectiveness of publicly sponsored VC is mixed like for other industrial policy interventions via private finance

[3] Andonov, Li, and Smeets (2025) provides an empirical analysis at a global scale focusing on the 30 largest of such institutions (see also Lerner (1996), Lerner (2013), Bernstein, Lerner, and Schoar (2013) and Bai et al. (2021)). Colonnelli, Li, and Liu (2024) and Beraja et al. (Forthcoming) analyze empirically role the government in the Chinese venture market.

[4] This has been linked to concentration on less dynamic mature firms (Biondi et al., 2023).

[5] Europe lags both in terms of investment volume and number of deals (Arnold, Claveres, & Frie, 2024)

[6] Our work relates to a rich literature related to VC Barkai and Panageas (2021), Davis et al. (2014), Gompers and Lerner (2004), Hellmann and Puri (2002), Kerr, Lerner, and Schoar (2014), Kerr and Nanda (2015), Kortum and Lerner (2001), Lerner and Nanda (2020), Samila and Sorenson (2011), Sorensen, Wang, and Yang (2014), and Sørensen and Yasuda (2023)

[7] This is not unique to Europe: González-Uribe (2020) documents state pension funds (which Hochberg and Rauh (2013) have local development concerns) have become the most important "Limited Partners" in VC in the US, accounting for around 30% of new funds committed to VC.

Investment Fund (EIF). This leading institution invests in private VC funds that independently select and monitor portfolio companies.[8] We find its policy mandate to support relatively mature "scale-ups" can have productivity-enhancing aggregate effects when targeting sectors or regions with strong financing frictions. However, for our calibrated values of the degree of financial frictions of Europe as a whole, reallocating funds towards early-stages first would be a cost-effective way to increase aggregate productivity.

In the first part of the paper, we digitize EIF's annual reports and match funds that received public commitments to VC deal databases, then track all subsequent investments made by EIF-backed funds. We also link VC deal micro data on all companies in Europe, enabling us to track firm outcomes both before and after receiving VC investments. This allows us to compare the magnitude, allocation, and impacts of government-supported VC activity against purely private market investments in Europe.

In the data, the gap between the European and the US VC markets is stark. Fewer companies receive VC funding and VC-backed European firms get less funding volumes. The European government via the EIF has taken steps towards expanding the aggregate supply of venture capital in Europe with the hope of closing these funding gaps. We document EIF-backed VC funds have become a large part of the European market and give increasingly larger funding amounts per firm.[9] European firms funded by an EIF-backed VC feature average funding levels resembling US ones.[10]

EIF-backed firms grow similarly to other VC-backed firms post-investment, but these

[8]The empirical literature finds a mix of underperformance of more direct interventions in VC (Cumming, Grilli, and Murtinu (2017) in Europe and Brander, Egan, and Hellmann (2010) in Canada) which may be due to the lack of selection and value creation of lower-tier VCs that collaborate with the government, since Colonnelli, Li, and Liu (2024) firm top VCs avoid the government to not constrain their investment decisions.

[9]These findings resonate with Brander, Du, and Hellmann (2015) who show globally that public interventions in VC can lead to more VC funding per enterprise and more VC-funded enterprises largely augmenting rather than crowding-out private VC finance, crowding-in larger volumes of capital known as "additionality". Leleux and Surlemont (2003) also find no evidence of crowding out and state "public involvement seems to cause greater amounts of money to be invested in the industry as a whole." In our conversations with policymakers, we learned they believe their main role is not to provide capital but to crowd-in private co-investors by alleviating information asymmetries through their extensive due diligence process.

[10]EIF-linked firms also more money independently of their size (controlling for age, sector, or region).

effects are the strongest when investing in young firms and not the old. Given the outsized impact on young firms one might expect policy to prioritize funds focused on early-stages, especially given how important the EIF has become in the financing of relatively large, young firms.[11]

In practice, however, the EIF—like many public VC investors in Europe and globally—prioritizes later-stage investments.[12] EIF-backed funds disproportionately target older firms relative to the broader VC market. Why?

Our discussions with policymakers behind the EIF — supported by our estimates of the EIF's own portfolio allocation — indicate an intentional focus on supporting later-stage "scale-ups" over early-stage "start-ups". This policy stance is rooted on the belief that large later-stage funding gaps remain while progress in closing early-stage funding gaps has been more substantial.[13]

In the second part of the paper, motivated by this evidence, we develop a model in the macro-development tradition with entrepreneurs subject to borrowing frictions of Buera, Kaboski, and Shin (2011), Midrigan and Xu (2014), and Moll (2014) among others.[14] Heterogeneous workers with business ideas may become entrepreneurs which can be venture financed by heterogeneous VC funds, which specialize in different stages of the firm life cycle. Funds intermediate money from a large institutional investor which

[11]PitchBook data shows almost 40% of 20-250 employee firms under 5 in Europe are linked to the EIF.

[12]Andonov, Li, and Smeets (2025) show similar patterns hold outside of Europe. Fuest et al. (2024) provide suggestive evidence that one of the VC-like arms of the EU government, the European Investment Council (EIC) provides funds to relatively mature firms instead of financing "disruptive" innovations and propose redirecting funds towards a new ARPA-like government agency in Europe and outsourcing VC activities to specialzied funds of the kinds we study here.

[13]In our analyses of VC-backed firm data in the current vintage of PitchBook, we observe disproportionately smaller number of later-stage firms vs early-stage ones in Europe vs the US. However, unlike research using prior PitchBook vintages World Economic Forum (2014), we do not observe that average funding amounts in later-stages vis-a vis early-stages are disproportionately lower relative to US levels.

[14]Many papers build on these early frameworks to study related questions to ours: Di Giovanni et al. (2023) study government procurements, Kochen (2024) study firm trade in PE, Peter (2019) studies Initial Public Offerings (IPOs) in Europe, and Gopinath et al. (2017) study financial frictions in Southern Europe. None study industrial policy via VC. Ando (2024) and Akcigit et al. (2022) also study VC in the context of models of firm dynamics but do not discuss industrial policy intermediated by VC funds in Europe. Acemoglu et al. (2018) study industrial policy in the US through subsidies and grants, but not indirect investments of the ones we study.

allocates money across funds following mandates.[15] We estimate this mandated allocation using EIF data and calibrate the rest of the model to match standard moments.[16]

Our main innovation in the model is inspired by the data, where EIF-backed firms raise more money independently of firm size and other firm-level measures. Thus, we allow the funding VC-backed firms can raise to depend not only on their own ideosyncratic constraints (i.e. the amount of capital they need to reach their productive potential) but also on the aggregate (constrained) supply of equity for different stages.

This new model ingredient highlights that government interventions can affect the overall volume of venture capital[17]. In turn, by expanding the overall supply of venture capital, entities like the EIF can end up lifting financing constraints unevenly across firms depending on the distribution of financing "gaps" along the firm age distribution.[18] These financing gaps in different stages — which are endogenous to the economic environment and central for the solution of the model — are crucial to the policy debate.[19]

Counterfactuals reveal our main result: industrial policy via venture capital can improve aggregate productivity, but implementation details matter. In particular, to maximize aggregate productivity, the share of funds allocated to funds — specialized across different life cycle stages, sectors, or regions — needs to depend on the degree of financial market imperfections.[20] We find that a high degree of financial frictions rationalizes the policy focus on mature firms.[21] Starting to invest in previously untapped markets

[15] We can also allow for multiple institutional investors with regional or sectorial mandates.

[16] These include the firm age distribution of economic activity and leverage

[17] We view this as a similar mechanism as "Prudent Man Rules" that happened in the US with the deregulation of public pension funds that led to their expansion as investors in VC (González-Uribe (2020)) or (de)regulation changes that affect the overall supply of venture capital like "Blue Sky Laws" (Ewens and Farre-Mensa (2020)) and other rule changes (Chen and Ewens (2021))

[18] Our theoretical mechanism for a volume increase of government funding in VC resonates with the empirical studies in Brander, Du, and Hellmann (2015) and Leleux and Surlemont (2003); however, little is known about life cycle stage asymetries.

[19] There are other attempts in the literature at modelling the use of public funding to crowd-in private capital via the decision making of Development Financial Institutions /textciteflammer2025economics

[20] Aggregate TFP is the benchmark measure in the macro-development literature following Hsieh and Klenow (2009); Hsieh and Klenow (2014) emphasize the importance of the firm life cycle in this context

[21] In fact, the model's "optimal" share of young firms targeted closely resembles the empirical share biased towards older firms. That is, the expansion of venture capital supply has disproportionately affected later-stage VC, as in Ewens and Farre-Mensa (2020).

with underdeveloped financial markets can yield large effects, but supporting later-stage VC there is necessary.[22] However, our model calls into question the ongoing policy shift towards "scale-ups" in more financially developed economies: increasing early-stage investments there could improve aggregate productivity.[23] To reap the full benefits of a "Big Push" in markets with milder financial frictions one needs to reallocate funds towards early-stage VC first before increasing them.[24] Indeed, in our baseline calibration, we find that reallocating budget towards early-stages but keeping the total amount spent constant produces aggregate effects of the same magnitude of increasing the amount of spending to try to do a “Big Push".

The theory built in this paper aims to overcome some of the drawbacks in the empirical literature using *ex-post* data surveyed in De Haas and González-Uribe (2024). In particular, our framework allows for evaluating the effectiveness of industrial policy via venture capital *ex-ante* via counterfactuals, in particular regarding effects on long-run, aggregate productivity which are difficult to capture using only empirical analyses. Our model shows these aggregate effects vary widely across institutional contexts, hinting at the role of varying degree of financial market incompleteness, heterogeneous funding volumes, and firm life cycle focus as potential explainations for the mixed empirical literature.[25]

[22]Our theoretical results resonate with the empirical findings of Cole et al. (2020), who use data on the International Financial Corporation argue "financial frictions have prevented the flow of capital from rich to poor countries, and that the persistence of impact investors' performance may rely on identifying or creating new markets that lack access to capital." However, the literature on impact investment (Cole et al. (2023), Jeffers, Lyu, and Posenau (2024), Barber, Morse, and Yasuda (2021), textcitezhang2021impact) hints that although in practice institutions such as these may be more able to target the right regions or sectors in need of capital, whether then they are able to expand the financing frontier rather than crowd-out private capital is contentious, perhaps due to political economy considerations (Dreher, Lang, and Richert (2019), Frigerio and Vandone (2020)).

[23]Our findings resonate with Howell (2017), who finds that even in the relatively financially developed US economy, government-provide grant awards to companies can alleviate financial frictions by crowding-in investments by private VCs that promote innovation. In the design of related policies, preserving a bottom-up approach is crucial (Howell et al. (2021)).

[24]Our work corroborates the important of the firm life cycle when trying to understand the aggregate, a point emphasized by Krusell, Thurwachter, and Weiss (2023) and Aragoneses (2023), especially when considering financial frictions as a limit to firm growth, as in Sterk, Sedláček, and Pugsley (2021), Ottonello and Winberry (2024), and Kochen (2024).

[25]The model also allows us to learn about inter-firm spillovers (in our model happening through factor prices and the endogenous funding "gaps") and let's us understand the distributional consequences through wealth inequality. We are currently exploring these and other angles with the model.

2 Institutional Setting & Data Sources

We describe data on the European private equity market and public investment in it.

2.1 Institutional Setting

We highlight 30-40% of new VC funds in Europe originate from government agencies.

European Private Capital Markets. In 2024, Mario Draghi published a report highlighting weaknesses in EU business dynamism, private investment, and productivity partly linked to a weakness of private equity markets.[26] European private capital markets systematically underfund firms at different stages of the life cycle, providing a lower amount of early-stage funding and less later-stage funding for growth. Behind these patterns there is likely: (a) a lack of risk capital supply for firms with good long term projects to invest, (b) a lack sufficiently good projects that require long-term risk finance perhaps due to the lack of supply, and (c) that the lack of later-stage financing discourages the creation of firms with growth perspectives.

Government Investment via the European Investment Fund (EIF). We document government agencies account for 30–40% of new VC investment in Europe, with the European Investment Fund (EIF) emerging as one of the largest players. As part of the European Investment Bank Group, the EIF operates under both financial and policy mandates to expand access to risk capital, particularly for SMEs. It invests indirectly through intermediaries—VC and PE funds, banks, and other financial institutions—allowing it to reach firms across all stages of development. This indirect model enables broad coverage of the innovation lifecycle, from early-stage to growth-phase firms. Other more direct or national investment initiatives (e.g., the European Innovation Council (EIC) or Bpifrance) are discussed in the Appendix.

[26] Draghi (2024). The report brought back to light unsolved issues that had been discussed ten year earlier by a World Economic Forum report World Economic Forum (2014)

2.2 Data Sources

We build a dataset on VC/PE backed European firms invested on by the government.

Reports on Government PE and VC Investment Portfolios. We digitized the European Investment Fund's (EIF) annual reports to obtain fund-level data on equity allocations, including recipient fund names and annual capital commitments. These equity investments—distinct from EIF loans or guarantees—have grown substantially over time: the EIF's annual equity allocation exceeded €5.6 billion in 2023, up from near-zero levels in the late 1990s (see Appendix).[27] The EIF's scale is comparable to major private investors: SoftBank invested approximately €4.8 billionglobally in 2023. It also exceeds the combined European investments of the top five sovereign wealth funds, the largest being Singapore's GIC, which invested €1.9 billion in Europe in 2024.[28]

Deal-Level Data from Private Equity and Venture Capital Markets. PitchBook provides detailed information on private equity and venture capital transactions, including deal date, company characteristics, investors, and deal size. We link this data to EIF investments through a two-step matching procedure based on fund names from EIF annual reports. This allows us to identify deals involving EIF-backed funds and compare them to purely private investments. The Appendix presents descriptive statistics on EIF-backed activity, and we benchmark our micro-level data against macro-level aggregates from an independent EU industry association.[29]

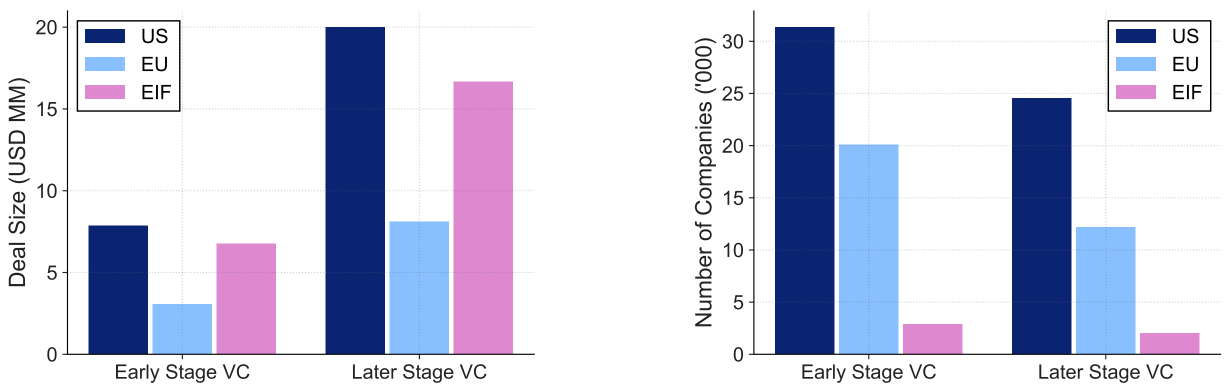
Micro and Macro Data on European Firms. Orbis provides panel data on European firms, including financials (sales, profits, assets, debt) and firm characteristics (age, size, employment, industry). To track firm outcomes before and after EIF-backed investments,

[27]This last year, total government agency commitments to PE in Europe were estimated at €8.3 billion, implying that the EIF accounted for a substantial share.

[28]We also digitized data on the European Innovation Council (EIC) using government records and Dealroom, but report these separately in the Appendix since they are of smaller scale due to their distinct investment model.

[29]We have also produced results based on CrunchBase, Dealroom, and Preqin, which are in the Appendix; we have these sources to be of lower quality relative to Pitchbook in terms of matching ratios observed in the European independent industry reports relative to Pitchbook.

Figure 1: *Size of Venture Capital Market in the US and the EU, 2010-2019*



Notes: This figure shows the number of companies funded and the average amount received by a funded firm in a year, broken down by the age of the firm. In each panel, we also show the corresponding statistic for firms in the EU which received investments from EIF-backed funds. The data are from PitchBook for the period 2010-2019. The sample is limited to the US and the EU, where the EU includes the set of countries included in the CompNet sample.

we link Orbis to PitchBook using firm names and locations, employing advanced text-matching techniques, including LLM-based embeddings. Finally, we use Eurostat and CompNet data to match regional and sectoral characteristics of EIF investments and calibrate our model using corresponding empirical moments.

3 Empirical Facts

In this section, we document three facts about industrial policy via venture capital in Europe: (1) the magnitude of government investment directed at the short-falls of the European VC market is large and (2) its allocation is skewed towards later-stage VC investments in relatively older firms (3) despite the fact that their reduced-form impact is only strong and persistent when investing in younger firms – a group which they are particularly large source of funds.

3.1 Weak European Private Capital Market & Public Investment

The size of VC markets between the US and the EU is stark: annual VC investments make up 0.7% of GDP in the US compared to only 0.2% of GDP in the EU[30].

Fact 1. In Europe, relative to the US, fewer companies receive VC funding (especially in later-stages) *and* each firm gets less funding. European companies with the EIF as an investor feature higher average funding levels closer to the US market.

Figure 1 shows the number of early-stage VC funded deals in the EU is about 2/3 of the number in the US; for later-stage VC funded deals, this number is half of that in the US.[31] The former is surprising since the US and the EU have similar startup rates. Remarkably, there are large differences in the average funding received by a firm in a year as well. In a second graph in the same figure, we show that, on average, EU firms receive only 40% of the venture capital that US firms receive across *both* early and later stages. The relative difference between early and late funding amounts is surprisingly similar EU vs US, suggesting the supply of venture capital per funded EU firm is depressed uniformly.[32]

Also in Figure 1, we highlight the number of deals funded by funds backed by the EIF and compare their average funding levels to the broader EU and US markets. While only around one out of size of EU VC deals are backed by the EIF,[33] these deals are on average closer to the US levels than the average EU deal: deals where the EIF is involved as an investor end up being twice as large on average than the average deal in Europe.[34]

[30] See (Arnold, Claveres, & Frie, 2024) 2024 IMF report. This macro-level difference also appears in micro data from PitchBook between 2010 and 2019

[31] Independent data from an industry association shows an even starker difference in the number of firms getting financed in later stages in Europe.

[32] Indeed, regardless of the data source we used, we found that on average receive between 2 and 3 times the funding in later stages as they do in earlier rounds.

[33] A proportion that seems to apply to global institutions of this kind, see Andonov, Li, and Smeets (2025)

[34] In the Appendix, we show that an even smaller share of EU VC deals are backed by the EIC, but these direct deals are significantly less well funded than those indirectly funded by the EIF, and tend to resemble more the typical EU deal. The difference in funding size between the EIF and the EIC seem especially stark for early-stage deals, where the EIF gives much larger amounts of money to younger firms.

We aim to evaluate the aggregate effects of this intervention.

The micro data also shows that despite the volume differences between the EU and the US, the two have surprisingly stationary and similar ratios of young v.s. old firms getting funded and the average funding deal size per firm. This hints at the technological parameters in the VC cost structure conditional on funding not being too different between the US and the EU, which could explain the strikingly similar proportions at which the industry allocates less money on average to a larger number of young firms. This could indicate that while the VC industry in the two continents works similarly, in Europe there is a lower aggregate volume of funding being dedicated towards VC.[35]

EIF-backed VC funds are not only a large part of the European market, but also give increasingly larger funding amounts via-a-vis non-EIF backed funds. In the Appendix, we document the importance of the EIF in the EU's VC and PE market and how this institution's investment has evolved over time. The Appendix shows EIF-backed funds accounted for a consistently large share of 30-40% out of the aggregate supply of early- or late-stage VC since the EIF's inception in the 1990s.[36] Further, the Appendix shows that their VC investments per firm has increase significantly since its early days, going from investing amounts comparable to the rest of the market to investing 3 times more per firm, consistent with our earlier findings.[37] In contrast to VC, the weight of the EIF in the EU's PE market is much more limited, representing under 10% of the overall supply of both buyout and growth funding and their PE investments are on average slightly smaller than those of the market.[38] Hence our focus on VC and away of PE.

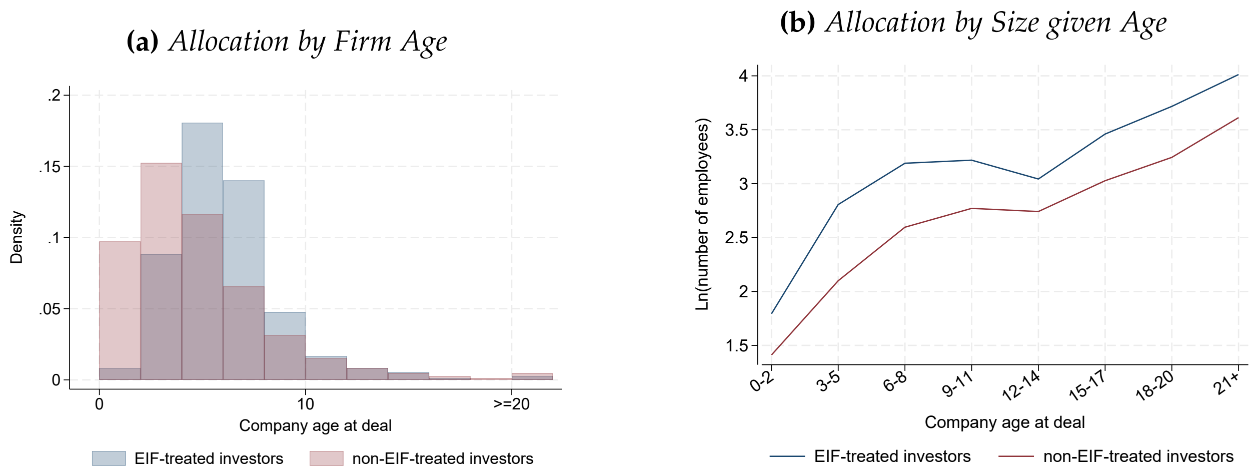
[35]One hypothesis we test in the model is wether allowing for large entities like the government or institutional investors to pour liquidity into the VC eco-system alone, effectively finding a way to reallocate currently-trapped savings into productive investment, could improve aggregate dynamism.

[36]While these numbers come from our EIF-Pitchbook linked sample, Figure 1 shows government agencies were the source of 37.4% of all European funding for VC in 2023 using data from an independent association in the European VC/PE industry.

[37]We confirm this rise in VC funding per firm holds among all stages of financing: seed, early, and later VC; thus, it is not due to a changing composition towards deals where funding sizes are larger. If anything, their weight in seed funding has increased.

[38]Again, we do not think these numbers are unique to Pitchbook, since alternative industry reports indicate government agencies are responsible for 7.5% of PE investment money in Europe in 2023.

Figure 2: *Share of EU Firms Funded by Age & Size | EIF vs. Market*



Notes: This figure shows the share of firms in each age bracket that received fundings from EIF-backed funds and non-EIF-backed funds; it also shows size conditional on age. Results are weighted by deal size to describe where the money goes. The data are from PitchBook for the period 2010-2019.

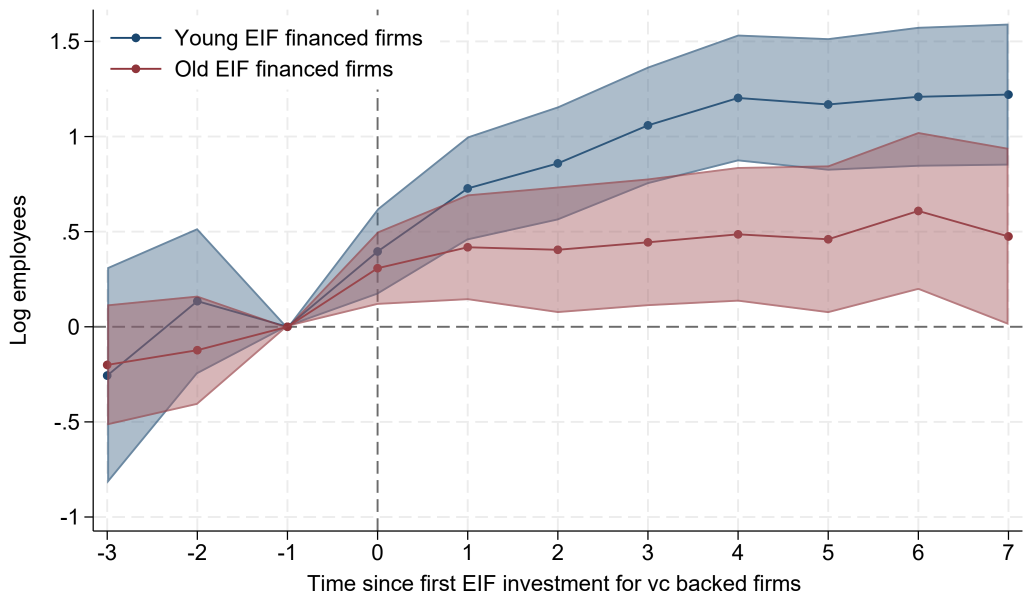
3.2 The Allocation of EIF Funds across Heterogeneous Firms

In this section, we compare firms receiving EIF funds with those that do not in order to understand how investments differ by the stage of the funding life cycle and firm size.

Fact 2. Relative to the rest of the market, EIF-backed VC funds end up investing in *older* firms. They also tend to invest in larger firms relative to the market, especially when investing in young firms in the early-stage.

In Figure 2, we show that firms backed by EIF-linked venture capital tend to be older at the time of the deal than those backed by non-EIF investors. In the Appendix, we also show the their of the budget allocated to each fund declines with the share of young portfolio companies in the fund (based on age at the time of the firm deal). However, we also observe EIF-backed firms are also systematically larger conditional on age, with this size-bias being seemingly stronger when investing in younger firms. Figure 2 confirms this using employee-based size brackets: EIF-backed funds allocate a greater share of capital to larger firms, but this bias is most pronounced in early-stage investments.

Figure 3: *Firm Dynamics Post EIF Investment on Young vs Old*



Notes: This figure shows a stacked diff-in-diff run separately for young and old firms using data on longitudinal employment from Pitchbook and EIF treatment indicators from annual reports.

In the Appendix, we show that EIF-backed firms account for nearly 30% of all employees at VC-backed firms in the EU, despite representing less than 20% of such firms. The disparity is more pronounced in specific firm categories: among early-stage VC-backed firms with 20–249 employees, EIF-backed firms represent roughly 40% of total employment. These patterns suggest that while the EIF does invest in older, larger firms, its role is especially significant for younger, larger firms.

3.3 Firm Dynamics Post VC Investment

We examine the dynamic firm-level effects of indirect public venture financing in the EU, focusing on EIF-backed firms relative to matched peers. We run a stacked (staggered) differences-in-differences specification on Orbis employment data, we define treatment by the timing of first EIF-linked investment. [39] Controls are selected via Propensity Score Matching based on observables like firm age, size, sector, and financial ratios, following standard practices in the private equity literature. We confirm parallel trends but treat our estimates as suggestive due to potential spillover effects.

Fact 3. EIF-backed firms experience strong, persistent post-investment growth when investing in young firms and weaker effects when investing in the old.

Figure 3 show EIF funding via private VC intermediaries significantly improves post-investment firm performance—especially when directed at young firms in the early-stages. These effects are persistent and robust across outcomes (e.g., revenue, valuation, productivity) and datasets (Orbis and Pitchbook). In contrast, late-stage investments in older firms yield more muted growth.[40] In Appendix Figure C.1 we observe a slightly statistically significant over-performance of firms financed by an EIF-linked VC relative to those financed by the rest of the private venture market, which we attribute to the higher EIF funding amounts documented above.[41]

3.4 Take-aways from the Data for the Model

The government-led EIF has aimed at expanding the aggregate supply of venture capital with the hope to close European funding gaps, effectively trying to undo the facts that fewer European companies receive VC funding and VC-backed firms get less funding

[39]

$$y_{ict} = \alpha_i + \alpha_t + \sum_{-L \leq t-c < -1} \beta_k^{\text{pre}} \, x_{i,c,t}^{\{c=t-E_i\}} + \sum_{0 \leq t-c \leq F} \beta_k^{\text{post}} \, x_{i,c,t}^{\{c=t-E_i\}} + X'_{ist}\theta + \epsilon_{it}$$

[40] These results echo the ones in Howell (2017) who found smaller early-stage grants awarded to firms by the US government had much more powerful effects than later grants awarded at later-stages; she interprets these results as early-on funding relaxing financing constraints, allowing entrepreneurs to experiment and develop a proof-of-concept

[41] In the Appendix, we compare the post investment dynamics of indirectly (EIF) versus directly (EIC including EASME) financed firms. It shows public investments intermediated via private VCs are nearly twice as effective at boosting firm performance relative to direct investments when government agencies choose firms. Venture investments directly chosen by the government also take much longer to translate into firm growth and half roughly half of the longer term impacts relative to those allocated by private VCs. This highlights the benefits of private intermediation relative to full public intervention when governments choose to engage in industrial policy via venture capital.

volumes relative to the US. EIF-backed firms — similar to other VC-backed firms – experience positive and persistent post-investment growth only if investments take place when firms are young. Given the outsized impact on young firms one might expect policy to prioritize funds focused on early-stages, especially given how important the EIF has become in the financing of relatively large, young firms.

In practice, however, there is a puzzle: EIF backs funds that disproportionately target older firms relative to the broader VC market. We conducted qualitative interviews with European policymakers behind the EIF that indicate there is an intentional priority on supporting later-stage "scale-ups" over early-stage "start-ups".[42]

Below we present a structural model where an institutional investor (the EIF) allocates equity investments to funds mandated to target different stages of the firm life cycle. In the model, whether the EIF wants to target early- or later-stages depends on the degree of financial frictions. When investing in regions with underdeveloped financial markets or high-tech sectors with difficult to collateralize assets, targeting some later-stage investments is not only not a bad idea, but it actually improves aggregate productivity relative to going all-in on early-stage investments.

4 Model

We develop an equilibrium firm dynamics model of venture finance with heterogeneous workers, entrepreneurs, and funds. Workers with business ideas may become entrepreneurs facing borrowing constraints they can partially overcome by equity investments from VC funds. VC funds, which specialize in different stages of the firm life cycle, intermediate money from an institutional investor. This investor, which could be the government, allocates a limited budget across funds with different mandates, shifting the supply of equity supply across different life cycle stages.

[42]This policy stance is rooted in the belief that later-stage gaps are larger—which we observe in the disproportionately smaller number of VC-backed later-stage firms vs early-stage ones.

4.1 Setup

Time is discrete, and the horizon is infinite. The model features three types of agents: workers, entrepreneurs, and funds.

Workers. Workers and entrepreneurs have some stock of assets a and productivity z, and derive utility $u(c)$ over consumption c. Workers gain the option to run a firm with probability ζ (exogenous for now). With some probability ϕ_0, they receive seed funding F_0 from VC markets which adds to their stock of next period's assets. ϕ_0 and F_0 are endogenous objects that will depend on the aggregate supply available for seed funding new entrants. Once funded, the state variable f' will track the funding history.[43]

Workers' value function subject to a budget constraint

$$
\begin{aligned}
v^w(z,a) \quad &= \quad \max u(c) + \beta(1-\zeta)\ \mathbb{E}_{z'|z}\left[v^w(z',a')\right] \\
&+ \quad \beta\zeta\,(1-\phi_0)\ \mathbb{E}_{z'|z}\, v_0^e(z',a',0) \\
&+ \quad \beta\zeta\,\phi_0\ \mathbb{E}_{z'|z}\, v_0^e(z',a'+F_0,f') \\
c \ &= wh(z) + (1+r)a - a'
\end{aligned}
$$

where $h(z)$ is an exogenous function that maps productivity to hours worked, w is the wage rate, a' denotes savings for the next period, and r is the interest rate.

Entrepreneurs. After entry, entrepreneurs will face different life-cycle stages, g[44]. $v_g^e(z,a,f)$ is the value function of a firm owned by an entrepreneur, and it depends on whether the firm has been funded in the past or not, given by status f; if the entrepreneur is unfunded, then $f=0$. Once the business idea arrives, with some probability η (exogenous for now), the entrepreneur continues to operate the firm, and with some probability $1-\eta$, the entrepreneur loses their business idea and the option to run their business, and becomes a regular worker.

[43] This state will determine the share of equity in the firm given up to outsiders by the entrepreneur.
[44] which could be firm age or coarser stage classifications

With some probability ϕ_g, it receives later-stage financing F_g from VC markets which depends on the stage at which they are in. Note that follow-on funding is allowed. The value function is given by the following subject to the budget constraint which incorporates the option of not operating the firm at no cost while retaining the idea.[45]

$$
\begin{aligned}
v^e_{g_-}(z,a,f) &= \max u(c) + \beta(1-\eta)\,\mathbb{E}_{z'|z}\left[v^w(z',a')\right] \\
&+ \quad \beta\eta\,(1-\phi_g)\;\mathbb{E}_{z'|z}\,v^e_g(z',a',f) \\
&+ \quad \beta\eta\,\phi_g\;\mathbb{E}_{z'|z}\,v^e_g(z',a'+F_g,f') \\
c &= \max\left[\pi(z,a,f), wh(z)\right] + (1+r)a - a'
\end{aligned}
$$

where $\pi(z,a,f)$ denotes profits from operating a firm with funding status f with productivity z and asset holdings a. Profits from operating a firm with funding status f are given by a function given a collateral constraint

$$
\pi(z,a,f) = (1-\tau(f))\max_{l,k}\left[y\,(z,l,k) - w\ell - (r+\delta)\,k\right]
$$

$$
\text{such that} \quad k \leq \lambda a
$$

where k and ℓ are the capital and labor inputs, respectively, τ is the share of firm owned by VCs in exchange for equity finance, and Z_e is the productivity of the private sector. Unfunded firms retain all of their profits. Note that firms are subject to an asset-based borrowing constraint, governed by the parameter λ.[46]

VC funding allows the most productive entrepreneurs to reach a level of assets that gets them in equal footing to compete with their wealthy counterparts that have a business idea of much lower quality.

[45] This allows for situations where the entrepreneur has effectively sold the entire business or situations where a is so low that the entrepreneur does not find profitable to work on the firm at all.

[46] In the appendix, we allow this parameter to be a function of firms' states such as g, for example, if older firms have less strict borrowing constraints due to reputation built.

Funds. Large institutions like the EIF allocate an exogenous flow spending G across different funds, and often seek to invest in funds with very specific and fixed mandates often determined by the different "pockets" where their budget comes from. [47]

We model $\mathcal{J}$ VC funds indexed by j in the economy which differ in the groups of firms g in which they focus. While these groups later include regions or sectors where the EIF needs to spend specific budget "pockets", for now we focus on different life-cycle stages.[48] Only constrained firms with positive financing needs will seek to be equity financed. Let N_g^c is the mass of constrained firms of type g[49].

Funds also differ in their scale and the number of portfolio companies in which they can invest in every period n_j. Each fund j needs to follow a pre-specify mandate X_{jg}

$$X_{jg} = \phi_{jg} \cdot N_g^c / n_j$$

where ϕ_{jg} is the probability that fund j funds firms of type g. Consistent with the data, funds may allocate to multiple groups with different weights. We use the matrix $\mathbf{X}$ to define the network of $\mathcal{J}$ funds to groups $\mathcal{G}$. Given these probabilities determined by the funds' mandates, constrained entrepreneurs will match funds with probability: $\phi_g = 1 - \prod_j \left(1 - \phi_{jg}\right)$.

The amount firms can raise will depend on their idiosyncratic funding needs as well as the overall supply of equity which will be affected by the mandates of funds in which a large institutional investor, such as the EIF, invest an exogenous budget.

[47] For example, one of the recent calls for interest from the EIF for VC funds operating in Slovenia states: *"The investment strategy shall be focused on innovative early stage companies with high growth potential. The Fund shall mainly focus on early stage initial investments and have the potential to follow-on in the next round. However, it could also allocate a small share of the Fund size to initial investments into "Series B" or "Series C" rounds provided appropriate opportunities occur."* Source: Call for Expression of Interest to select a financial intermediary to be funded within the scope of the Slovene Equity Growth Investment Programme (SEGIP)

[48] For example, coarse groupings such as early or later stage, or fine as Series B or Series C as in the Slovenian example above

[49] For example, the number of financially constrained firms in Slovenia seeking early stage funding. This is an endogenous object that depends on the underlying distribution of firms of different g and whether they are financially constrained given their z, a: $N_g^c = \int 1[k^*(z) \geq k(a)] dD_g(z, a, f)$

Absent financing constraints, $k^*(z)$ would be the optimal capital choice of a firm with ability z. Let $F^*(z,a)$ be the external financing needs of an entrepreneur with ability z and assets a. Given the constraint:

$$F^*(z,a) = \max\{0, k^*(z) - k(a)\}/\lambda$$

Let $\bar{F}_g$ be the average funding "gap" for the N_g^c constrained firms of type g:

$$\bar{F}_g = \int F^*(z,a) \cdot dD_g(z,a,f)/N_g^c$$

Each fund receives share s_j of the institutional investor's budget

$$B_j = s_j(\mathbf{X}) \cdot G$$

Funding firms raise depends on two factors: (1) firms' financing needs at the micro level F^* and (2) funds' financing capacity towards stage g at the macro level ω_g.[50]

$$F_g(z,a) \quad = \quad \omega_g \cdot F^*(z,a)$$

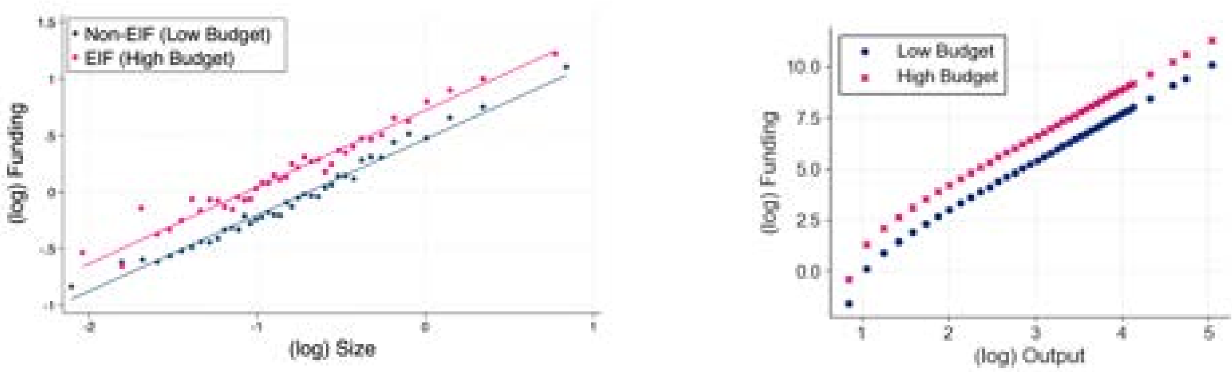
Letting $\mathbf{f} = \{\bar{F}_g\}_{\forall g}$ be the set of endogenous funding gaps across groups (i.e. life-cycle stages, sectors, regions), we can define ω_g as the funding capacity that depends on the mandates across funds with different g specialization and the overall budget G.

[50] ω_g reflects that funds must allocate budgets according to pre-specified mandates:

$$B_j = \sum_g \phi_{jg} \cdot F_{jg}$$

Figure 4: *Average Funding of EIF-backed Firms is Higher given Firm Size*

(a) *Data* **(b)** *Model*



Notes: This figure shows both in the data and in the model, firms funded by an EIF-linked investor receive higher average funding amounts independently of their size; we view the higher intercept as the average ω_g. First, using PitchBook from 2010-2019, it shows the average funding per firm (deal sizes) as a function of firm size for EIF v.s. non-EIF backed firms in a binscatter plot residualizes age, sector, and region; a similar pattern hold unconditionally. Underlying this is that funds backed that the EIF are larger in terms of funding, giving more money per firm.

$$\omega_g := \omega_g\left(\mathbf{X}, \mathbf{f}, G\right) \quad \propto \quad \sum_j \frac{X_{jg} \cdot \left[s_j(\mathbf{X}) \cdot G\right]}{\sum_g X_{jg} \cdot \bar{F}_g}, \quad \forall g$$

In the model, a higher budget G translates into higher funding amounts through ω_g independently of the firms' idiosyncratic funding needs determined by z, a. In the data, we indeed see *EIF-backed firms raise more money independently of firm size*. In Figure 4, we highlight *how* deal size increases with firm size for EIF and non-EIF linked firms, discussing the similar slope versus the different intercept in this relation. Surprisingly, regardless of whether the fund is linked to the EIF or not, deal size tracks firm size in the same fashion, indicating both types of investors are equally able to allocate relatively more money to firms that likely have higher productivity z. However, EIF-linked funds allocate larger funding amounts to firms on average, and thus, EIF-backed firms command a funding premium independent of firm size.[51]

[51]We are working out alternative micro-foundations for F^*. However, what's crucial for our analyses is the presence of ω_g disconnected from the idiosyncratic funding needs, which could accommodate

Table 1: *Externally Calibrated Parameters*

Parameter	Description	Value
η	Pr(Firm Lose Idea)	8%
Z_e	Entrep productivity	1
Z_c	Corporate productivity	0.6
α	Capital elasticity	0.33
δ	Depreciation rate	0.06
β	Discount factor	0.9115
σ	Inter-temporal Substitution	2
ν	Returns to scale	0.8
$1-\tau$	Insider share per round	0.85
γ	Productivity persistence	0.8
$\underline{z}$	Pareto Min Productivity	1.11

Equilibrium. We solve for w and r clearing labor and capital markets.

$$\int h(z)\cdot D_w(z,a)+\sum_g\int h(z)\cdot D_g^e(z,a,f)=L_c+\sum_g\int l(z)\cdot D_g^e(z,a,f)$$
$$\int aD_w(z,a)+\sum_g\int aD_g^e(z,a,f)=K_c+\sum_g\int k(z,a)D_g^e(z,a,f)$$

G enters directly in goods markets clearing, by Walras Law, and indirectly through it's effect on the asset distribution of funded firms and equilibrium prices. Further, we solve for a fixed point on "financing gaps" investors take as given, which determines $\omega_g(\mathbf{X},\mathbf{f},G)$, which depends on endogenous firm policies and the distributions. We add a competitive representative public firm (a "corporation") with a constant return to scale technology given by $Y_c = Z_c K_c^{\alpha} L_c^{1-\alpha}$. Details will be in the Appendix.

4.2 Calibration

We consider a baseline European economy without industrial policy $G=0$.

alternative forms. In the Appendix we present an alternative F^* tied to the ex-ante value of the company rather than the short-fall in capital demand.

Table 2: *Internally Calibrated Parameters*

Parameter	Description	Value	Moment	Model	Data
λ	Borrowing Const.	2.686	Debt/Assets Ratio	48.4%	48.5%
ζ	Pr(Worker has Idea)	0.009	% of Young Firm	37.7%	35%
η_z	Pareto Tail Prod.	3.289	Employment % at Young	20.9%	20%
X	Mandate Matrix J x G	$[0,1]$	% Firms Funded by Age	[0,1]	[0,1]
s_j	Fund Portfolio Shares	$[0,1]$	% Funding by Stage	[0,1]	[0,1]

Tables 1 and 2 present the parametrization of the model.[52] We choose the business idea destruction rate $\eta = 8\%$ and idea creation rate $\zeta = 1.6\%$ to target the firm exit and entry rates in EuroStat (note in the model, since ζ is the share of workers that get ideas, the firm entry rate is ζ times average workers per firm). We choose $\lambda = k/a$ for all firms from Orbis between 1997 and 2007 to target the ratio of capital to assets in the data. We use a CRRA utility function $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$ with a standard value for the EIS. We set β to target a desired level of the interest rate in the 1997-2007 period in Gopinath et al. (2017) . For the worker human capital to ability relation we use $h(z) = \log(z)$. We use a decreasing returns to scale Cobb-Douglas production function

$$y(z,l,k) = z \cdot Z_e \cdot \left(k^{\alpha} l^{1-\alpha}\right)^{\nu}$$

with a standard δ and α. We normalize the productivity shifters to make sure corporate firms are larger than entrepreneurs. In our model, long run life cycle growth profile of firms since entry is determined by η_z, z_0, λ, and ν. Entrepreneurial skill evolves according to the following law of motion where $z_{it+1} = z_{it}$ with probability γ and $z' \sim \mathcal{P}(z_0, \eta_z)$ with probability $1-\gamma$, where $\mathcal{P}$ is Pareto distribution with scale parameter z_0 and shape parameter η_z $CDF(z) = 1 - (z/z_0)^{-\eta_z}$. Note that we have to calibrate η_z (describing the productivity process) and ν (the degree of returns to scale) jointly so that the following factor is non-negative: $M = \frac{\eta_z}{\eta_z - \frac{1}{1-\nu}}$.

[52] We use a Nelder-Mead Simulated Method of Moments (SMM) algorithm to calibrate the model. We internally calibrate the parameters of the productivity process and the borrowing constraint to make the model match data moments of the firm age distribution of economic activity and leverage.

Skill Dynamics. z evolves according to a law of motion with γ persistence

$$z_{i,t+1} = \begin{cases} z_{i,t} & \text{with probability } \gamma \\ z' \sim \mathcal{P}(z_{min}, \eta_z) & \text{with probability } 1-\gamma \end{cases}$$

$\mathcal{P}$ is a Pareto distribution with scale parameter z_{min}, shape parameter η_z, and density

$$f(z) = \eta_z \cdot z_{min}^{\eta_z} \cdot z^{-\eta_z - 1}$$

Standard targeted moments. The model reproduces well the distribution of firms by age and (importantly) its size-weighted counterpart, the distribution of employment across firms of different ages. In EuroStat data, roughly 35% (65%) of firms are "young" ("old") defined as being less (more) than 5 years old, while in the model 37% (63%) of firms are young (old) in equilibrium. In the data, because size increases with firm age, roughly 20% (80%) of employees work at young (old) firms, while 22% (78%) in the model. Since in this simple version of the model employment is proportional to output, the distribution of output is similarly skewed towards older firms. We also match aggregate leverage.

Novel fund parameterization. For now, estimate parameters for the fund of funds from the data. We first fix a set of characteristics for each fund, e.g. X_{j0} share of investments into early stages (pre-seed, seed, and Series A) made by a fund 8 years after the EIF's investment. We choose 8 because that is the typical life-cycle of a fund accounting for time raising money. We then estimate $s_j(X)$ from the data on the portfolio shares of the EIF across different funds with different stage preferences.

Equity share parametrization. For now, we choose something simple: every time a firm gets equity funded through follow-on investments, it must give up a share of it's equity, so $1 - \tau(f) = (1-\tau)^f$. We calibrate this so that after 5 times founded ($f = 5$ is the maximum we allow) the entrepreneur retains 44% of the equity in the company.[53]

[53]We are working on a version where $\tau(f) = f$, i.e. where we keep track of only the equity share given

5 Industrial Policy via Venture Capital Counterfactuals

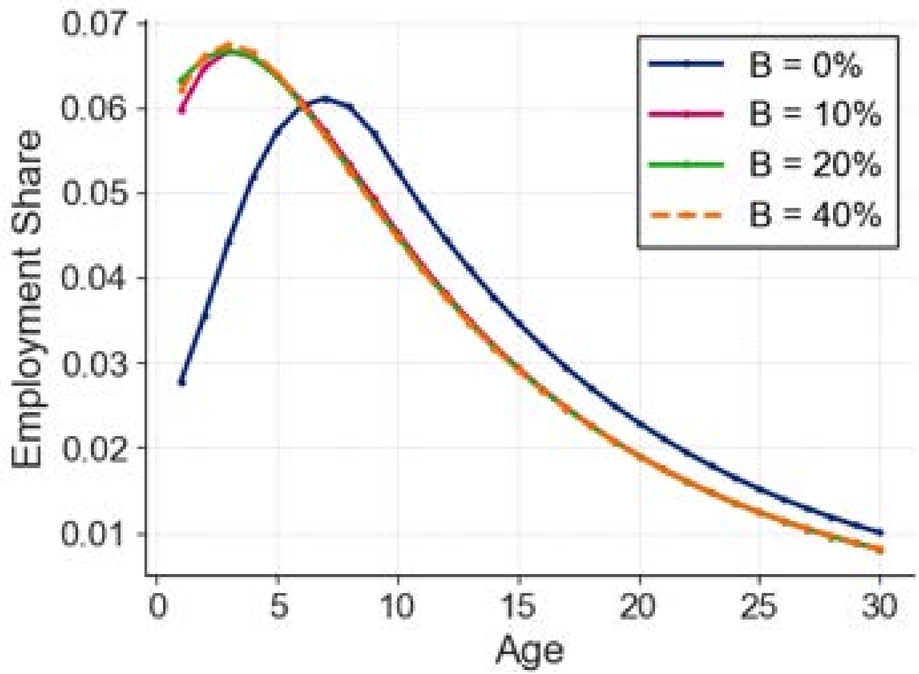
Armed with our calibrated model, we now turn to evaluating industrial policy in which governments investment is intermediated via private venture capital funds. We examine the long-run aggregate productivity and distributional effects of expanding and reallocating the supply of venture capital via such government investment. We highlight key results from our simulations, redoing all our analyses for different levels of financial market imperfections, captured by varying parameter λ. We contrast results for the European average as a whole to markets with high financing frictions which we view as present in less financially developed countries or sectors where assets cannot be collateralized well or risky cashflows are far in the future.

First, we do a “Big Push" counterfactual, where we increase budget-financed spending $G = B$ by different amounts given the allocation $s_j(X)$ which we hold at the calibrated current investment portfolio in the data. This is motivated by proposals in Draghi (2024) which argues for public spending to lead a “Big Push".[54] Second, we do a “Reallocating budget" counterfactual, where for any budget G we change the allocation $s_j(X)$ focusing on a shift in early versus late-stage focus via X_{j0}. This is motivated by the proposal in Fuest et al. (2024) who argue that the current allocation of funds is too skewed towards older firms. Third, we do a “Big Push” while “Reallocating budget" counterfactual where we increase spending while reallocating its stage target.

up, which we re-calculate in every round of financing based on the share of equity given up that makes the entrepreneur indifference between raising or not.

[54]We perform counterfactuals relative to a baseline economy without such policy in place which could be thought of as the period prior to the mid-1990s before the EIF existed. One can view the pre 2010 as a period with less funding capacity where the EIF committed a relatively modest amount of about 500 million euros per year on average to equity investments mainly through VC funds. One can also view the post-2010 as a period of higher funding capacity where the funding of the EIF has rise to over 5 billion euros per year. However, since the 2027 budget is currently being discussed with the potential to consolidate the size of the EIF amidst fiscal tensions in Europe, one can view our low vs high budget counterfactuals as letting the EIF manages the budget from other entities like the EIC, shifting resources from direct to indirect industrial policy.

Figure 5: *Employment Share by Age*



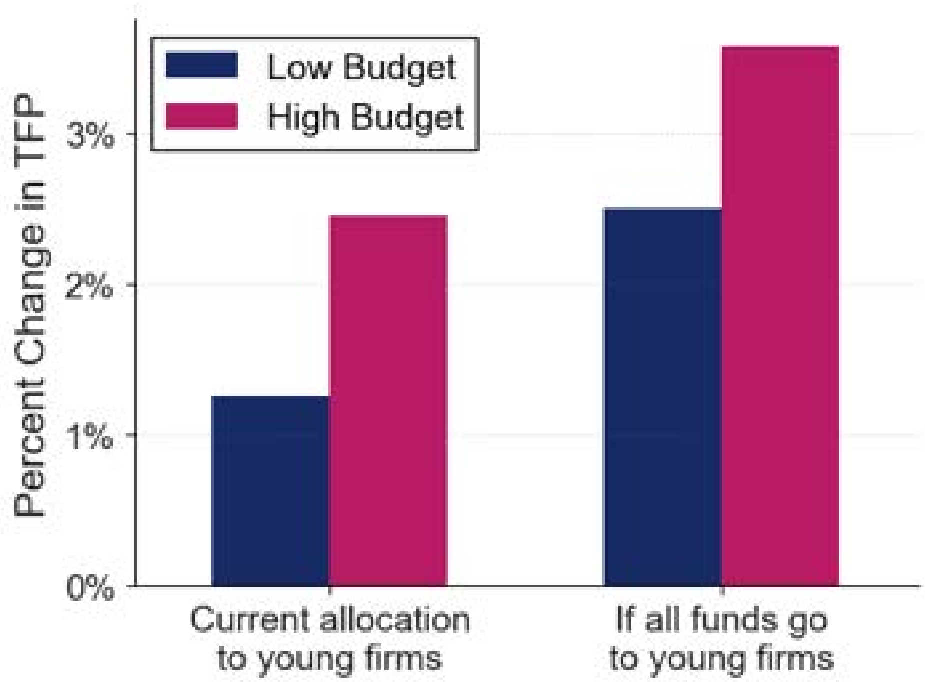
Notes: This figure shows employment share by firm age under different budgets $B = G$.

5.1 Increasing versus Reallocating Spending

Given the asset-based borrowing constraint, young firms that have not yet had the time to accumulate assets are more likely to be constrained than older firms. As a direct consequence of the expansion of venture capital supply, even when relatively biased towards later-stages, the borrowing constraint of young firms is relaxed too, allowing them to expand relative to the baseline scenario. Figure 5 shows an indirect shift in the distribution of economic activity towards young firms. Directly re-allocating the age composition of investments towards young firms further amplifies this effect. Note these policies help undo the pattern that European economic activity has reallocated away from young firms, as documented in Biondi et al. (2023).

Figure 6 shows the aggregate productivity (TFP) effects of industrial policies at the baseline calibration. Consistent with our previous discussion, keeping the current al-

Figure 6: *Changing Spending vs Allocation of Industrial Policy via Venture Capital*



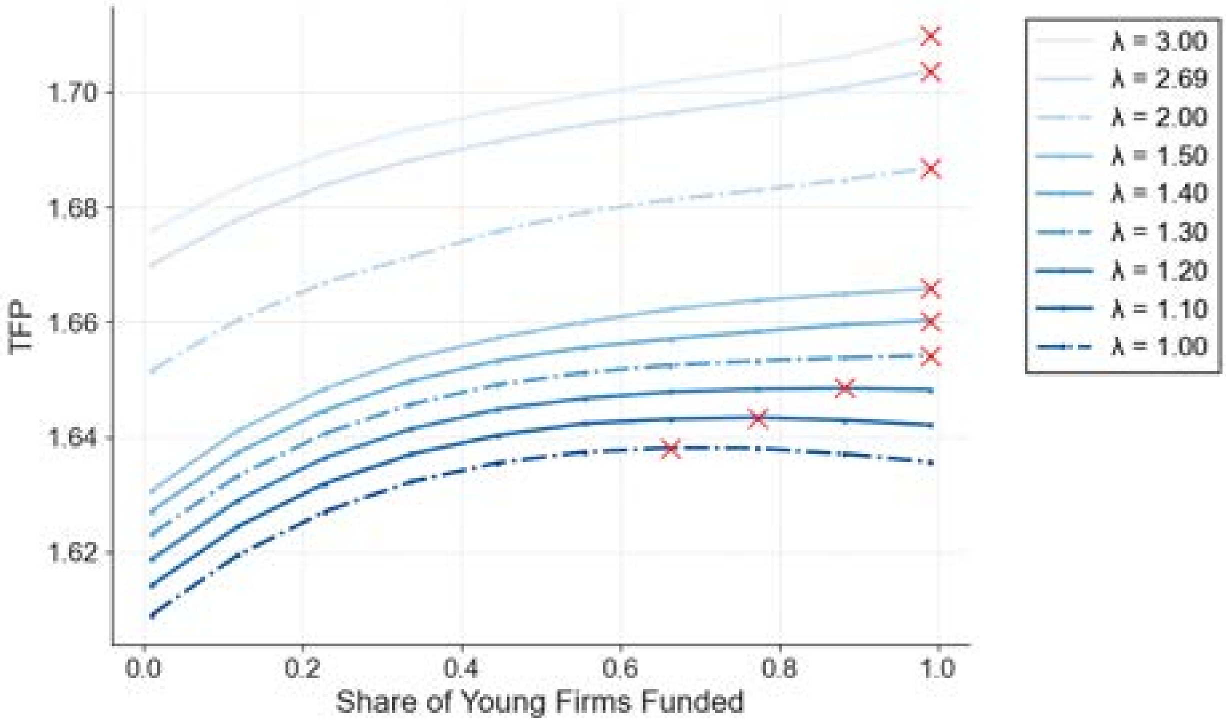
Notes: This figure shows model counterfactuals of changes in the budget for industrial policy via venture capital and changes in the allocation of funding across funds of different life cycle stage focus at the baseline calibration.

location but doubling the amount of spending performing a "Big Push" doubles the TFP gains from 1.25% to 2.5% relative to baseline.[55] Surprisingly, "reallocating budget" towards early-stages but keeping the total amount spent constant produces aggregate effects of the same magnitude.[56] Thus, this indicates that in the baseline calibration for the European economy, it would be more cost-effective to reallocate the current budget of industrial policy via venture capital to early-stage investments before continuing to increase it. Doubling spending when reallocating towards early-stages triples its effects.

[55] In the graph, this corresponds to High Budget + Current allocation to young firms

[56] In the graph, this corresponds to: Low Budget + If all funds go to young firms

Figure 7: *Aggregate Productivity*



Notes: This figure shows simulations of aggregate productivity as a function of the share of young firms financed, the early-stage mandate X_{j0}, for different degrees of financial frictions λ.

5.2 Industrial Policy via VC and Financial Market Imperfections

In the baseline calibration, with mild financial imperfections, the strongest benefits come from the reallocation of investment towards early-stages. In markets with more financial imperfections, the productivity impacts of reallocating investment towards younger firms gets muted and provide a rationale towards focusing on more mature "scale-ups".

Figure 7 plots aggregate TFP in economies with different degrees of financing constraints and allocations to early-stage investment (for a given budget).[57] The figure highlights again that in economies with relatively high λ, such as in our baseline calibration, policies that go "all in" towards early-stage investing maximize aggregate TFP.

[57] Higher λ improves aggregate productivity a la Midrigan and Xu (2014).

However, Figure 7 shows that as the degree of financing frictions increases, focusing resources on later-stage financing to some degree is beneficial for aggregate productivity. Indeed, in extreme cases where $\lambda = 1$, there is a hump-shape relation between how much young firms are targeted and aggregate TFP. This may justify why we see a substantial amount of funding being directed towards the later-stages, i.e. "scale-ups".

A central contribution of our paper is to identify the existence of this share and the hump-shaped relation between the share of young firms financed and aggregate productivity that appears in markets where financial frictions. Our model implies a form of "fiscal policy rule" of sorts for the conduct of industrial policy via venture capital. This rule, meant to maximize aggregate productivity, prescribes to vary the allocation of funds targeted towards early or laters-stage VC as a function of the degree of financial frictions of the different segmented sectors and regions in which investors operate. Beyond a certain threshold of financial market imperfections, targeting exclusively early-stage investments maximizes aggregate productivity.

Figure B.1b in the appendix revisits the example above with a lower λ. It shows that the aggregate TFP effects of investing markets where bank financing is more difficult (where misallocation and marginal revenue products of capital are the highest) are 2.5x higher than in more developed markets even at the baseline allocation and low budget.[58] However, further expansions in the supply of venture capital in less financially developed markets and reallocation towards younger firms may yield muted increases in aggregate TFP (or even declines) that might not justify the cost of this fiscal expansion. Surprisingly, the improvements in aggregate TFP that come as a result of increasing budget and reallocating towards the young may be much larger in more developed financial markets. A "Big Push" that also "reallocates budget" towards the early-stages improves the TFP gains in financially developed markets by nearly 3x (from 1.25% to 3.5%) while in developing financial markets by 1.33x.

[58] This is consistent with the empirical findings in Andonov, Li, and Smeets (2025) comparing developed and developing countries globally.

5.3 Discussion of Some Preliminary Policy Implications

Industrial policy via venture capital can improve aggregate productivity. However, our model shows the optimal investment allocation across VC funds — specialized in different stages, sectors, or regions — depends on degree of financial market imperfections. To reap the full benefits of a "Big Push" in markets with milder financial frictions one needs to reallocate funds towards early-stage VC first before increasing them. Starting to invest in previously untapped markets with underdeveloped financial markets can yield large effects, but supporting later-stage VC there is necessary.

Reallocate Funds First Before Increasing Them in Developed Markets. In financially developed economies, like the European average, it is more cost-effective to shift existing industrial policy funds towards early-stage companies. The above counterfactuals point to the fact that even smaller investments can go a long way in less financially developed markets. In markets with less financing constraints, where a lot of the funding goes, it could indeed be more cost-effective to reallocate the current budget to early-stages before continuing to increase it. These quantitative findings are consistent with the policy proposal discussed in Fuest et al. (2024) and the reduced-form regression evidence presented in the empirical section. Altogether, they call into question whether the policy focus on "scale-ups" should be sustained in regions or sectors where borrowing is easier, as shifting allocations towards early-stage investing there would improve aggregate productivity. Indeed in our baseline calibration focusing investments precisely towards relatively productive younger firms, which are the furthest away from their optimal size, tends to deliver robust productivity increases on aggregate.

Optimal Investment Strategy Depends on Degree of Financial Market Imperfections. The ideal allocation of capital is not one-size-fits-all. In markets with significant financial frictions (e.g., less-developed regions or sectors with intangible assets), a continued focus on financing more mature "scale-ups" is justified. Importantly, our model shows that the focus on markets with a high degree of financial frictions provides a rationale for the existing policy focus on "scale-ups" of mature firms. If policy-makers believe most markets they target have a λ closer to 1 than the one reflected in the calibration, "scale-up" financing is not a bad idea; indeed Figure 8 shows in most European countries, this form of industrial policy targets a share of young firms that is not 1.[59] The model yields conclusions that counter results from reduced-form diff-in-diff regressions because the latter are not equipped to handle the anticipation and selection effects that are crucial from a theoretical standpoint. Indeed, we find that when financial frictions are high, one needs to target later-stage financing and not just early-stages to reap the full benefits of the intervention.[60] If early-stage funds are given but these are not enough for firms to be unconstrained in later-stages, highly productive entrepreneurs are still not going to find it optimal to operate a firm that will not scale, and the effects of these interventions will be muted.[61].

Starting to Invest more Financially Imperfect Markets Yield High Effects. Even small investments can have a large impact in less-developed financial markets where capital constraints are more severe. Given the impacts relative to a baseline with no policy in markets with high financial frictions—less developed regions or sectors with more intangible assets—our model would indicate focusing resources there would be beneficial.[62] We are developing theoretical methods to identify untapped sectors (or regions) with stronger financial market imperfections where investing in funds (or helping develop a VC ecosystem) there would yield the largest improvements in aggregate productivity.[63]

[59] Except for Germany, it does not seem to be the case that in more financially developed countries the share of investment in young firms increases, something we are exploring further.

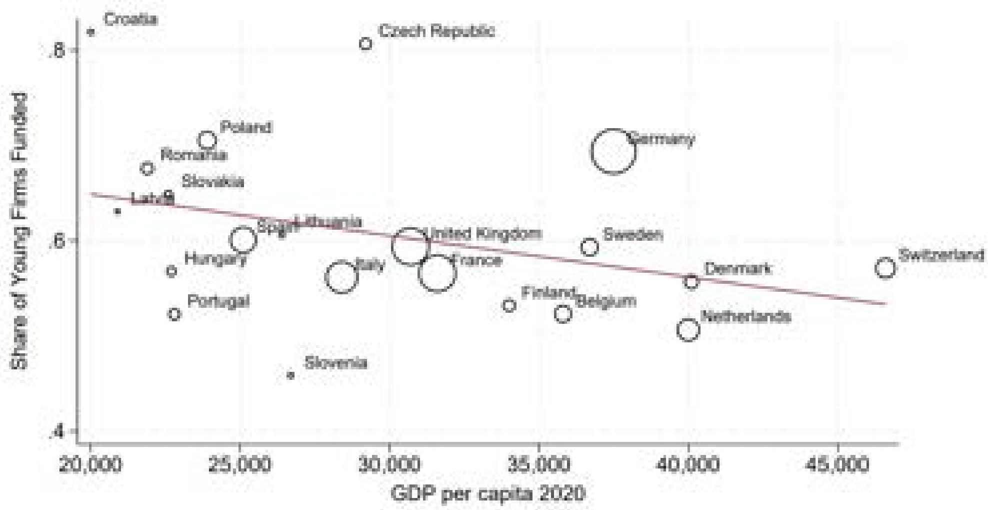
[60] We are working on identifying which sectors and regions are the ones where directing investment there yields the largest aggregate TFP effects (i.e. using survey measures of financing constraints) to understand market-specific targeting.

[61] These results might change when allowing for things like technology adoption decisions in the early stages which we are currently exploring

[62] This theoretical conclusion of our model complements the empirical findings in Andonov, Li, and Smeets (2025) who argue institutions that engage in industrial policy via venture capital is most effective in developing countries, where stronger market failures — such as frictions to access capital as we study here – leave more room for impact

[63] This echoes the call from De Haas and González-Uribe (2024) and Fuest et al. (2024) to increase investment in so called high-tech, disruptive sectors

Figure 8: *Early-stage Focus by Country GDP Per Capita*



Notes: This figure shows the relationship between the share of young firms funded by the EIF and GDP per capita of the different European countries. It weights countries by size.

A "Big Push" Can Work Well in Developed Financial Markets if Also Reallocated. If a large budget increase (a "Big Push") is fiscally possible, it can generate substantial aggregate productivity gains in developed markets, but only if the new funds are also reallocated towards early-stage companies. Whether these policies are cost effective at all and whether the government wants to do this directly through financing, or indirectly by undoing the regulations that impair large, later-stage investors is a question we leave for future iterations of this paper.[64] Our counterfactuals show that if the budget allows for a "Big Push" to be made, one might not only want to focus on the least developed markets. When properly targeting young firms, expansions of early-stage financing in more developed areas can have large aggregate effects.[65]

[64] These may relate to frictions in the integration of capital markets, taxation of exits, or other regulatory barriers that prevent flows to risk capital.

[65] There are countervailing effects of these policies we are currently exploring:For example, they shift economic activity towards younger firms, which on average are less productive, which may result in a lower TFP. Additionally, these policies may discourage investment among unfunded firms, and therefore, lower growth over their life cycle.

6 Conclusion

This paper investigates the allocation and impact of industrial policy investments by the European government via venture capital (VC) markets in Europe, where it makes up 30-40% of the total VC investments. We rely on data on an agency, the European Investment Fund (EIF) that has become a key player in the VC market in Europe.The EIF follows an indirect approach by investing in private VC funds who then select and fund firms. The EIF has become a large source of equity capital for relatively large, young European firms, and young firms indirectly financed by the EIF experience the most positive and persistent dynamics. In contrast, the impacts of investments into older firms quickly dissipate. Despite that, the portfolio of the EIF, like the ones of many similar institutions around the globe, is skewed towards older firms away from early-stages. Why? Qualitative interviews with policymakers shows this tilt is intentional in order to boost supply of capital for more mature "scale-ups" hindered by financial frictions.

Motivated by these puzzling facts, we build a model of firm life-cycle dynamics in which the EU government invests in venture capital. We use this model to shed light on the role of EU industrial policy in the presence of financial frictions. In particular, we conduct policy experiments in the model to shed light on the aggregate and distributional effects of a government-sponsored venture capital supply shock as proposed by a recent report by Mario Draghi. Consistent with the empirical evidence, we show that such a shock reallocates resources towards young firms that outgrow their borrowing constraints and expand their output. In general, the net effects of industrial policy intervention through VC funds on aggregate output and TFP are nuanced and depend on the details of the implementation and the economic environment.

In this paper, we highlight the stark differences in European private capital markets relative to the US and study one industrial policy solution. These striking differences may have important implications for the long-run trajectory and performance of firms in these markets, and may partially explain recent concerns about the decline in business dynamism in Europe[66]. This lack of private capital supply in the EU may have various origins we leave for future work, such the lack of capital market integration (since VCs in one country still face regulatory burdens in raising and investing funds in other EU countries) or the concentration of the excess household savings Europe in the hands of institutions (e.g. banks) invested lower-risk assets and preventing them from reaching firms ready to invest.

[66]See Biondi et al. (2023) for a recent discussion of the decline in business dynamism in Europe

References

Acemoglu, D., Akcigit, U., Alp, H., Bloom, N., & Kerr, W. (2018). Innovation, reallocation, and growth. *American Economic Review*, *108*(11), 3450–3491.

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

Ando, Y. (2024). *Dynamics of High-Growth Young Firms and the Role of Venture Capitalists*.

Andonov, A., Li, A., & Smeets, P. (2025). Do development financial institutions create impact through venture capital investments? *Available at SSRN 5101408*.

Aragoneses, M. (2023). The firm life cycle origins of the aggregate investment puzzle. *Available at SSRN 4863038*.

Arnold, N., Claveres, G., & Frie, J. (2024). *Stepping Up Venture Capital to Finance Innovation in Europe*. International Monetary Fund.

Bai, J., Bernstein, S., Dev, A., & Lerner, J. (2021). *The dance between government and private investors: Public entrepreneurial finance around the globe* (tech. rep.). National Bureau of Economic Research.

Barber, B. M., Morse, A., & Yasuda, A. (2021). Impact investing. *Journal of Financial Economics*, *139*(1), 162–185.

Barkai, S., & Panageas, S. (2021, October). *Value without Employment* (w29414). National Bureau of Economic Research. Cambridge, MA.

Beraja, M., Peng, W., Yang, D. Y., & Yuchtman, N. (Forthcoming). Government as Venture Capitalists in AI. *Entrepreneurship and Innovation Policy and the Economy*, *Vol. 4*.

Bernstein, S., Lerner, J., & Schoar, A. (2013). The investment strategies of sovereign wealth funds. *Journal of Economic Perspectives*, *27*(2), 219–238.

Biondi, F., Inferrera, S., Mertens, M., & Miranda, J. (2023). Declining Business Dynamism in Europe: The Role of Shocks, Market Power, and Technology. *Jena Economics Research Papers*.

Brander, J. A., Du, Q., & Hellmann, T. (2015). The effects of government-sponsored venture capital: International evidence. *Review of Finance*, *19*(2), 571–618.

Brander, J. A., Egan, E., & Hellmann, T. F. (2010). Government sponsored versus private venture capital: Canadian evidence. In *International differences in entrepreneurship* (pp. 275–320). University of Chicago Press.

Buera, F. J., Kaboski, J. P., & Shin, Y. (2011). Finance and Development: A Tale of Two Sectors. *American Economic Review*, *101*(5), 1964–2002.

Cengiz, D., Dube, A., Lindner, A., & Zipperer, B. (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics*, *134*(3), 1405–1454.

Chen, J., & Ewens, M. (2021). *Venture capital and startup agglomeration* (tech. rep.). National Bureau of Economic Research.

Cole, S., Jeng, L., Lerner, J., Rigol, N., & Roth, B. N. (2023). *What do impact investors do differently?* (Tech. rep.). National Bureau of Economic Research.

Cole, S., Melecky, M., Mölders, F., & Reed, T. (2020). *Long-run returns to impact investing in emerging markets and developing economies* (tech. rep.). National Bureau of Economic Research.

Colonnelli, E., Li, B., & Liu, E. (2024). Investing with the Government: A Field Experiment in China. *Journal of Political Economy*, *132*(1), 248–294.

Cumming, D. J., Grilli, L., & Murtinu, S. (2017). Governmental and independent venture capital investments in europe: A firm-level performance analysis. *Journal of corporate finance*, *42*, 439–459.

Davis, S. J., Haltiwanger, J., Handley, K., Jarmin, R., Lerner, J., & Miranda, J. (2014). Private Equity, Jobs, and Productivity. *American Economic Review*, *104*(12), 3956–3990.

De Haas, R., & González-Uribe, J. (2024). Public policies for private finance. *Available at SSRN 4989844*.

Di Giovanni, J., García-Santana, M., Jeenas, P., Moral-Benito, E., & Pijoan-Mas, J. (2023). *Buy Big or Buy Small?: Procurement Policies, Firms' Financing, and the Macroeconomy*.

Draghi, M. (2024). *The future of European competitiveness: Part A competitiveness strategy for Europe*.

Dreher, A., Lang, V. F., & Richert, K. (2019). The political economy of international finance corporation lending. *Journal of Development Economics*, *140*, 242–254.

Ewens, M., & 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.

Frigerio, M., & Vandone, D. (2020). European development banks and the political cycle. *European Journal of Political Economy*, *62*, 101852.

Fuest, C., Gros, D., Mengel, P.-L., Presidente, G., & Tirole, J. (2024). EU Innovation Policy.

Gompers, P. A., & Lerner, J. (2004). *The venture capital cycle*. MIT press.

González-Uribe, J. (2020). Exchanges of innovation resources inside venture capital portfolios. *Journal of Financial Economics*, *135*(1), 144–168.

Gopinath, G., Kalemli-Özcan, Ş., Karabarbounis, L., & Villegas-Sanchez, C. (2017). Capital allocation and productivity in south europe. *The Quarterly Journal of Economics*, *132*(4), 1915–1967.

Hellmann, T., & Puri, M. (2002). Venture Capital and the Professionalization of Start-Up Firms: Empirical Evidence. *The Journal of Finance*, *57*(1), 169–197.

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

Howell, S. T. (2017). Financing Innovation: Evidence from R&D Grants. *American Economic Review*, *107*(4), 1136–1164.

Howell, S. T., Rathje, J., Van Reenen, J., & Wong, J. (2021). *Opening up military innovation: Causal effects of reforms to us defense research* (tech. rep.). National Bureau of Economic Research.

Hsieh, C.-T., & Klenow, P. J. (2009). Misallocation and manufacturing tfp in china and india. *The Quarterly journal of economics*, *124*(4), 1403–1448.

Hsieh, C.-T., & Klenow, P. J. (2014). The life cycle of plants in india and mexico. *The Quarterly Journal of Economics*, *129*(3), 1035–1084.

Jeffers, J., Lyu, T., & Posenau, K. (2024). The risk and return of impact investing funds. *Journal of Financial Economics*, *161*, 103928.

Juhász, R., Lane, N., & Rodrik, D. (2024). The New Economics of Industrial Policy. *Annual Review of Economics*, *16*(1), 213–242.

Kalemli-Ozcan, S., Sorensen, B., Villegas-Sanchez, C., Volosovych, V., & Yesiltas, S. (2015). *How to construct nationally representative firm level data from the orbis global database: New facts and aggregate implications* (tech. rep.). National Bureau of Economic Research.

Kerr, W. R., Lerner, J., & Schoar, A. (2014). The consequences of entrepreneurial finance: Evidence from angel financings. *The Review of Financial Studies*, *27*(1), 20–55.

Kerr, W. R., & Nanda, R. (2015). Financing innovation. *Annual Review of Financial Economics*, *7*(1), 445–462.

Kochen, F. (2024). *Equity Financing in a Banking Crisis: Evidence from Private Firms*.

Kortum, S., & Lerner, J. (2001). Does venture capital spur innovation? In *Entrepreneurial inputs and outcomes: New studies of entrepreneurship in the united states* (pp. 1–44). Emerald Group Publishing Limited.

Krusell, P., Thurwachter, C., & Weiss, J. (2023). *Upwardly Mobile: The Response of Young vs. Old Firms to Monetary Policy*.

Leleux, B., & Surlemont, B. (2003). Public versus private venture capital: Seeding or crowding out? a pan-european analysis. *Journal of Business Venturing*, *18*(1), 81–104.

Lerner, J. (1996). The government as venture capitalist: The long-run effects of the sbir program.

Lerner, J. (2013). The boulevard of broken dreams: Innovation policy and entrepreneurship. *Innovation Policy and the Economy*, *13*(1), 61–82.

Lerner, J., & 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), 237–261.

Midrigan, V., & Xu, D. Y. (2014). Finance and Misallocation: Evidence from Plant-Level Data. *American Economic Review*, *104*(2), 422–458.

Moll, B. (2014). Productivity losses from financial frictions: Can self-financing undo capital misallocation? *American Economic Review*, *104*(10), 3186–3221.

Ottonello, P., & Winberry, T. (2024). *Capital, Ideas, and the Costs of Financial Frictions*.

Peter, A. (2019). *Owning Up: Closely Held Firms and Wealth Inequality*.

Samila, S., & Sorenson, O. (2011). Venture Capital, Entrepreneurship, and Economic Growth. *Review of Economics and Statistics*, *93*(1), 338–349.

Sorensen, M., Wang, N., & Yang, J. (2014). Valuing Private Equity. *Review of Financial Studies*, *27*(7), 1977–2021.

Sørensen, M., & Yasuda, A. (2023). Impact of Private Equity. In *Handbook of the Economics of Corporate Finance Vol 1: Private Equity and Entrepreneurial Finance (Elsevier)*.

Sterk, V., Sedláček, P., & Pugsley, B. (2021). The Nature of Firm Growth. *American Economic Review*, *111*(2), 547–579.

Wing, C., Freedman, S. M., & Hollingsworth, A. (2024). *Stacked difference-in-differences* (tech. rep.). National Bureau of Economic Research.

World Economic Forum. (2014). *Enhancing Europe's Competitiveness: Fostering Innovation-driven Entrepreneurship in Europe*. World Economic Forum.

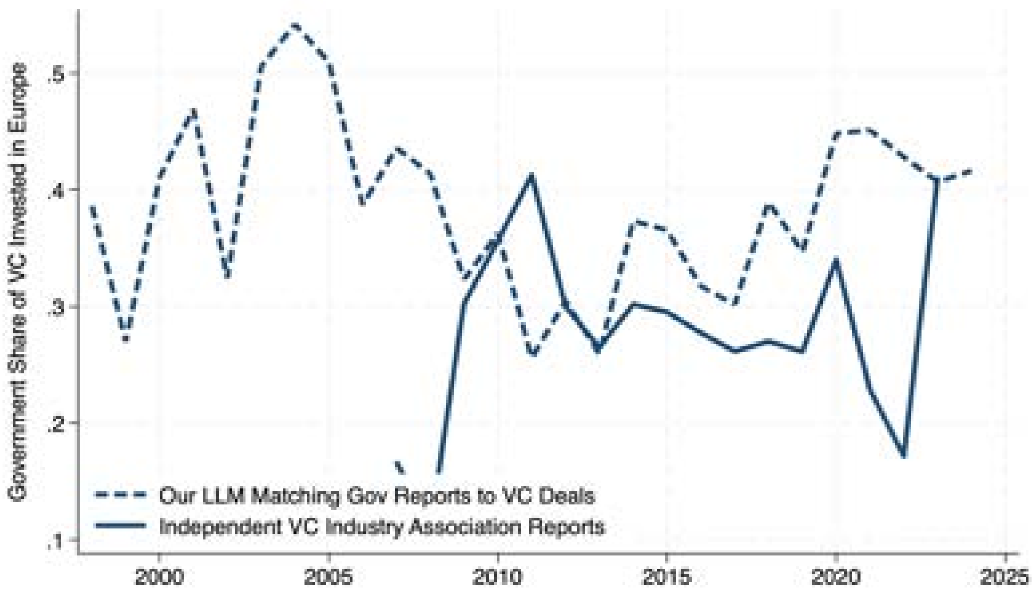
Appendix

A Data: Setting, Descriptive Stats, and Additional Facts

A.1 Institutional Setting & Data Sources

Assessing the weight of European government agencies in VC. We used data from InvestEurope (www.investeurope.eu), which provides an overview of the aggregate picture of the private capital industry in Europe. In their reports, they assess the size of "government agencies" as a source of VC funding in Europe. We show their weight relative to the overall amount of VC investment is substantial, of around 1/3 of the overall market across years, in Figure A.1. In qualitative interviews with a representative from InvestEurope we learned these numbers include both indirect and direct investments by multi-national or national agencies. In the current version of the paper we emphasise a multi-national indirect investor, the EIF, which invests as a "passive" limited partner without actively picking and monitoring companies. We are in the process of expanding our analyses to include national investment agencies (known as National Promotion Banks as well as Development Financial Institutions) in Europe; preliminary analyses suggest a lot of their investments are much more "direct" in nature. To confirm the size of government agencies in VC in Europe, we performed independent analyses using "deals" associated with different national promotion banks across different countries in Europe, which we tracked in PitchBook – BPI France, CDP Italy, ICO Spain, KfW Germany, BBB UK, SFPI Belgium, FMO Netherlands, ALMI Sweden, OEKB Austria, FINNVERA Finland, VACK Denmark, SBCI Irland, SNCI Luxembourg, SZRB Slovakia. We also added VC investments by the European Commission and the European Innovation Council (EIC), described below. Overall, the picture is clear and similar to the estimates of the IndustryEurope reports.

Figure A.1: *Government Agencies' Weight in the European VC Market: Share of VC Investments Linked to the Government in Europe*



Notes: For the first measure, we match annual reports on the VC funds where the EU government invests through its leading investment funds to micro data on VC investors and deals, and shows how much out of every euro raised in Europe for VC is backed by the government. The second measure shows our own calculations from independent industry report macro data showing the weight of investments from government agencies into all new, classifiable VC funds in Europe. These data sources and methodology used will be described in the next section.

EIF annual reports, EIF institutional details and evolution of investments. We accessed annual reports in the following link, downloaded them, and digitized them: https://www.eif.org/news_centre/publications/all/. Figure A.2 provides a snapshot of these reports. We referred to the EIF website[67] for institutional details on what the EIF does and their mission. We also have spoken with several EIF officials about their activities, providing qualitative insights into our quantitative analyses. The EIF states "Our central mission is to support Europe's small and medium-sized businesses (SMEs) by helping them to access finance. To this end, we aim at satisfying existing and future market needs by designing innovative financial products addressed to our partners (banks, guarantee, leasing and microfinance institutions, private equity and venture cap-

[67] https://www.eif.org/what_we_do/index

Figure A.2: *Example of fund and investment identified in the Annual Reports*

Table 3 – equity investments signed in 1997

Date of signature	Name of fund	Country of management	Amount invested (million)	ECUm*
EIF own resources				
9.1.97	Sofinnova Capital II	France	FRF 19.5	2.97
15.1.97	Prelude Trust plc	UK	GBP 2	2.74
25.4.97	MTI Three B Ltd. Partnership	UK	GBP 2	2.85
30.4.97	Alta Berkeley V C.V.	UK	ECU 3	3.00
16.5.97	Baltic Rim Fund Limited	Sweden	USD 3.4	2.95
26.6.97	Capricorn Venture Fund N.V.	Belgium	BEF 84.6	2.08
22.10.97	Strategic European Technology N.V.	Germany	NLG 6.5	2.92
30.10.97	SPEF pre-IPO European Fund	France	ECU 3	3.00
17.12.97	Kennet I Limited Partnership	UK	GBP 2	2.96
			Total	*25.47*

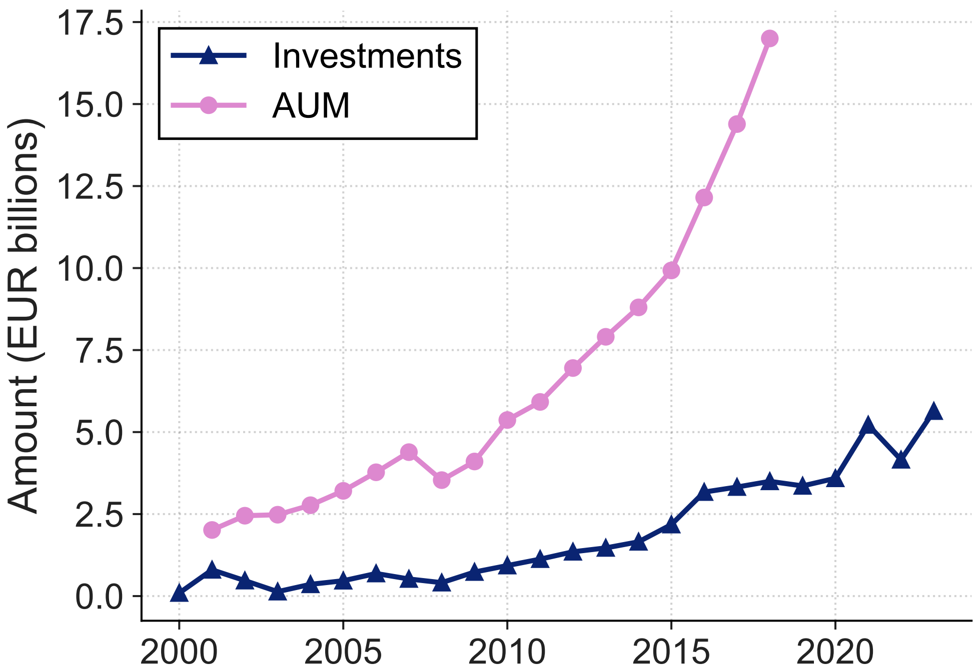
Notes: Here we present a snapshot of equity investments from the 1997 annual report.

ital funds, among others), acting as our financial intermediaries. [...] While our equity instruments aim to improve the availability of risk capital for high-growth and innovative SMEs, we also target the debt requirements, as many SMEs seek finance through this more traditional route." In our paper, we focus only on the equity investments side; we leave the study of their guarantee/debt portion of their investments for future work. Their indirect investments through private PE and VC funds, i.e. the EIF's annual equity allocation, have increased dramatically over time, noting it exceeded €5.6 billion in 2023 from near-zero levels in the 1990s. This is shown in Figure A.3.

EIF descriptive statistics and additional plots. We graphically provide descriptive statistics on the EIF portfolio and its evolution relative to the overall European market as shown in Figures A.4 to A.7. These figures jointly illustrate that:

- EIF's VC investments per firm have significantly increased since its inception and that EIF-backed funds (with a large part of the funds coming from private investors and national promotion banks that co-invest with the EIF) consistently accounted

Figure A.3: *"Indirect" Investments by the European Innovation Fund (EIF): Investments and Assets Under Management (AUM) of the EIF*



Notes: This figure shows the total amount of capital allocated to the European Investment Fund's (EIF) equity investments and the total assets under management of the EIF. The data are from the EIF's annual reports. This figure plots the AUM and annual commitments into VC and PE by the EIF. It shows a dramatic increased after 2010.

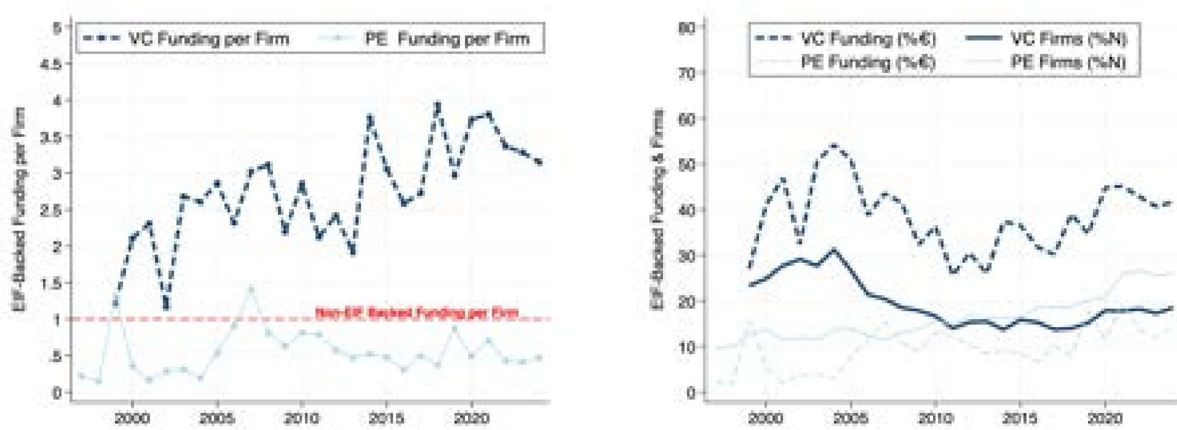
for 30-40% of the aggregate supply of early- and late-stage VC since the 1990s.

- This increase in investment per firm is linked to investments into larger funds as the EIF scaled up, with more capital per fund. This higher investment per firm is present regardless of firm characteristics for VC investments: firms with the same pre-money valuation or revenues (and other characteristics such as sector or country) receive higher funding amounts if their VC has the EIF as an LP. This funding "premium" is not present among PE investments.

- The EIF's budget allocation to a fund declines with the share of young portfolio companies in that fund. While this portfolio bias towards older firms is there, the EIF is an important source of funding for relatively large, young European firms.

Figure A.4: *Evolution of Average Deal Size and Magnitude VC vs PE: Government-Backed VC and PE Financing in the EU*

(a) *EIF-backed Investment per Firm* **(b)** *Share of EIF-backed Investment & Firms*

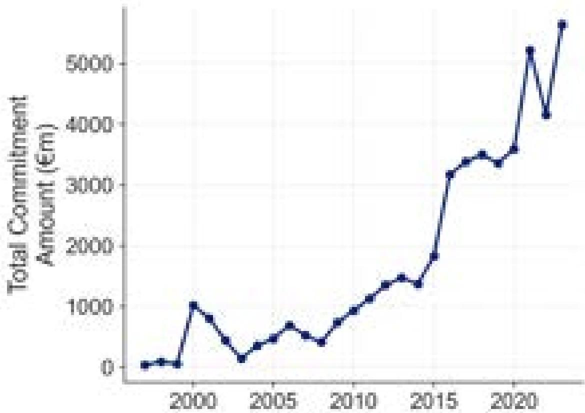


Notes: The first panel plots the share of aggregate investment and firms financed that are linked to the EIF within a given investment class (VC or PE). The second panel shows the rising funding per firm for firms that receive funding from the EIF relative to firms that were not linked to the EIF within a given investment class (VC or PE). The data are from the EIF's annual reports (first panel) and the reports linked to Pitchbook (second panel).

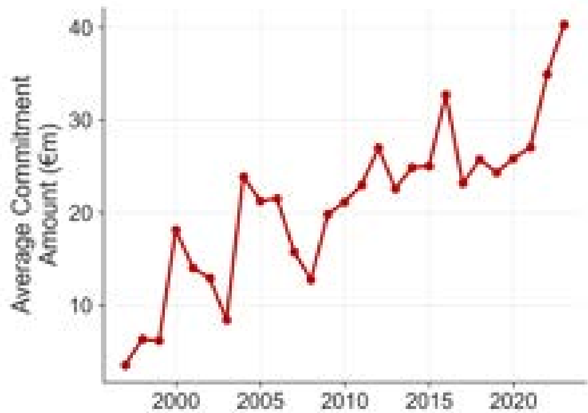
EIF-backed firms account for nearly 30% of all employees at VC-backed firms in the EU, and that among early-stage VC-backed firms with 20-249 employees, EIF-backed firms represent roughly 40% of total employment. VC-backed companies like Mistral AI, which fall in this category, seem to be the norm, not the exception.

Alternative data sources and rationale for using PitchBook We performed the same analyses using data from CrunchBase, Dealroom, and Preqin instead of PitchBook. While qualitatively very similar, we found both the coverage – raw and in terms of match rates with outside data sources – and the quality of variables available in PitchBook for Europe to be much better. Indeed, in our experience with both private VCs and the EIF, PitchBook is the most used source of private deals which is why we focused on it for our main analyses. In future iterations we will expand this appendix.

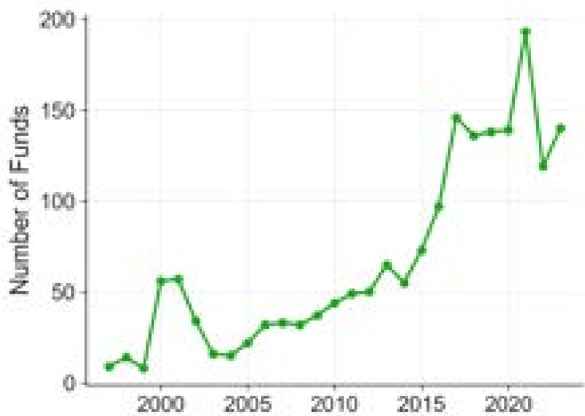
Figure A.5: *EIF Fund Investment Amounts and Allocation*



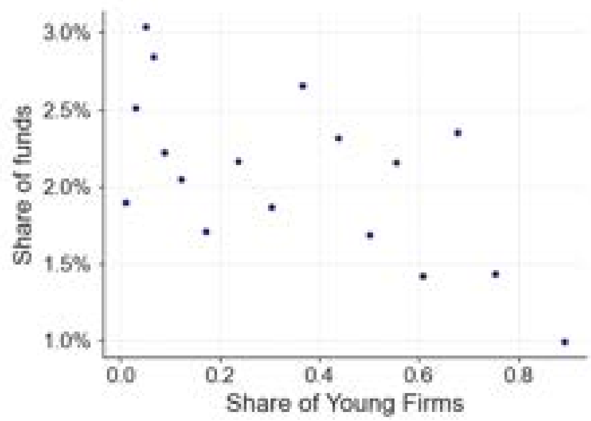
(a) *Total Commitment by Year*



(b) *Average Commitment by Year*



(c) *Number of Funds by Year*

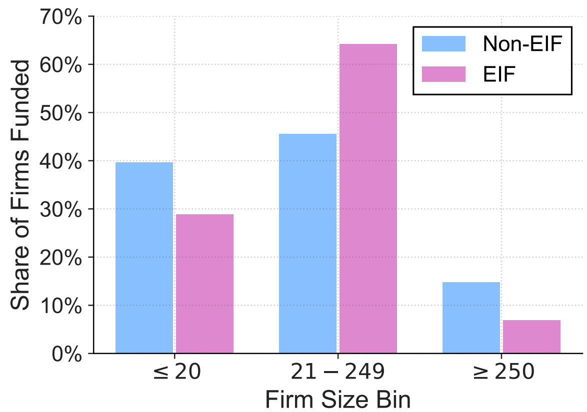


(d) *Budget allocation across funds*

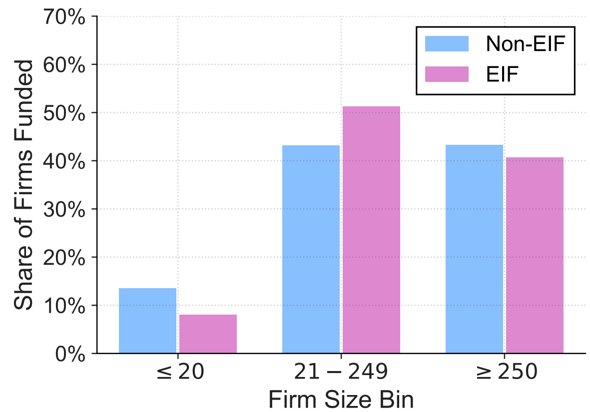
Notes: The top panels show the evolution of EIF's total and average commitments per fund over time. The bottom left panel shows the number of funds the EIF invested in each year. The bottom right panel shows how EIF allocations to funds vary by the share of young firms in the portfolio of each fund that received money from the EIF. The data are from EIF annual reports. For the bottom right panel, we match Pitchbook data on the share of young firms in each fund to the EIF's annual reports. This last figure shows how budget shares of the EIF vary by the share of young portfolio firms in each invested fund; it highlights that higher budget shares are allocated to funds with less young firms, indicating a bias away from early-stages.

Figure A.6: *EIF Allocation by Stage and Size: Share of EU Firms Funded by Size | EIF vs. Market*

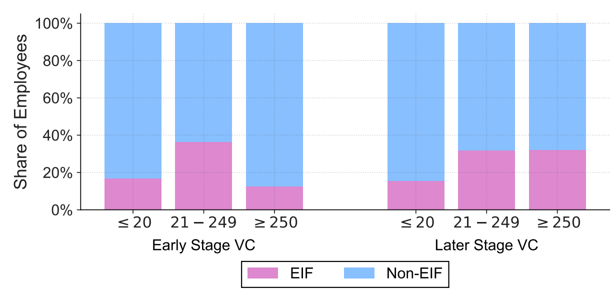
(a) *Early-Stage VC*



(b) *Later-Stage VC*

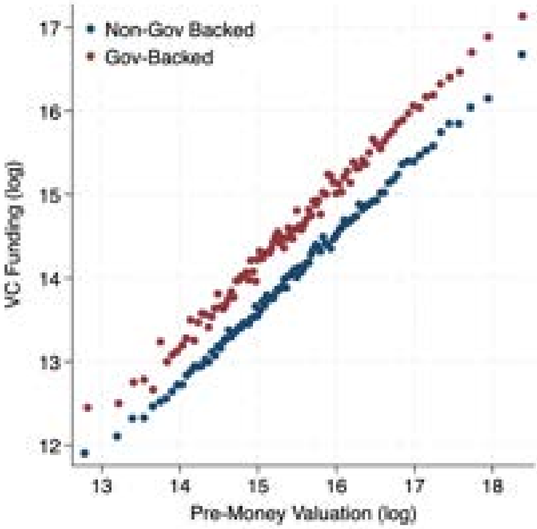


(c) *Share of Employees in Deals Backed by the EIF*

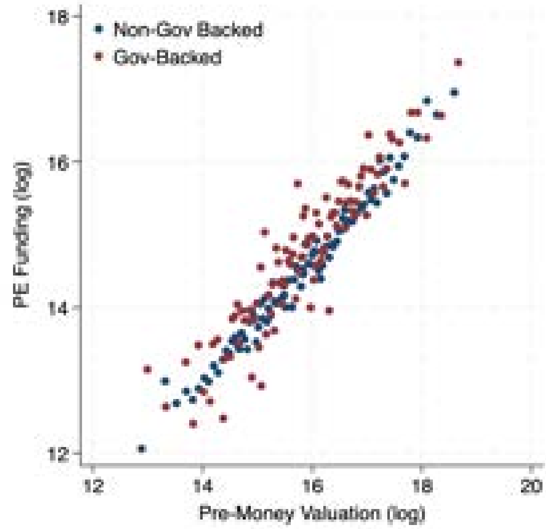


Notes: This figure shows the share of firms in each size bracket that received fundings from EIF-backed funds and non-EIF-backed funds. The data are from PitchBook for the period 2010-2019. The later figure shows the share of employees at firms involved in deals backed by the EIF in each size bracket and funding stage.

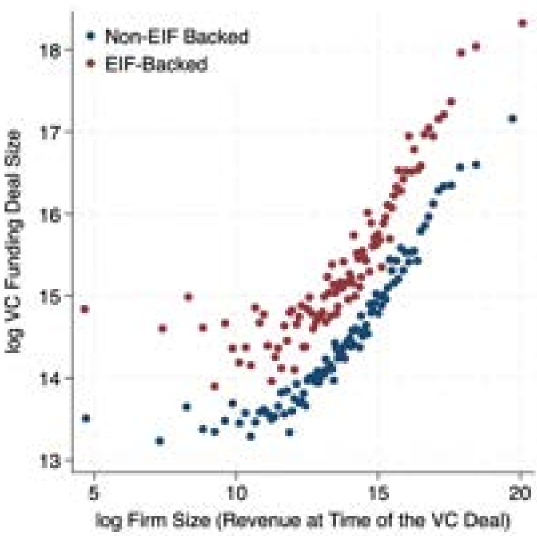
Figure A.7: *Average Funding of EIF companies is Higher Conditional on Size for VC but not PE Investments*



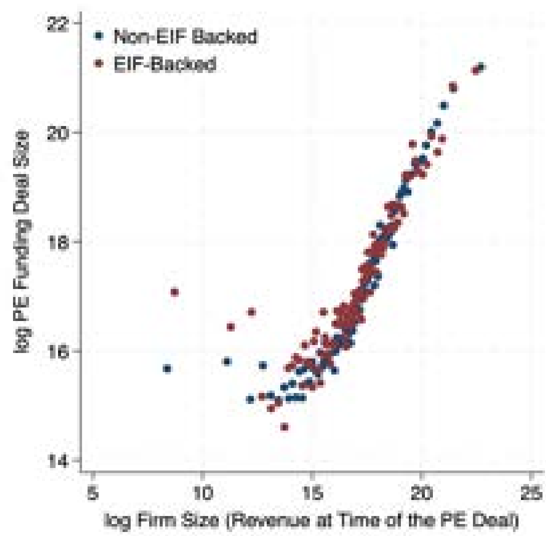
(a) *VC Funding vs Valuation*



(b) *PE Funding vs Valuation*



(c) *VC Funding vs Revenues*



(d) *PE Funding vs Revenues*

Notes: This figure shows the average funding per firm (deal sizes) as a function of firm size for EIF v.s. non-EIF backed firms. It restricts attention to VC investments. The binscatter plot residualizes age, sector, and region; a similar pattern hold unconditionally. Underlying this is that funds backed that the EIF are larger in terms of funding, giving more money per firm. The data are from PitchBook for the period 2010-2019. We show similar patterns hold for sales and pre-money valutaion. It shows the higher investment conditional on firm characterstics is only present in VC and not in PE.

B Model Details and Additional Counterfactuals

B.1 Further results with the baseline model

Corporate Public Firm and General Equilibrium In addition to the heterogeneous entrepreneurs, we allow for a corporate public firm with a constant returns to scale technology, making zero profits, and facing no borrowing frictions.

$$Y_c = ZZ_c K_c^{\alpha} L_c^{1-\alpha}$$

The purpose of this ingredient is to aid with the aggregation that helps clearing asset and labor markets following the literature who use a similar trick. The solution to the labor and capital demand from this public corporation is standard:

$$r_t = \alpha Z_t Z_{ct} \left(\frac{K_{ct}}{L_{ct}} \right)^{\alpha - 1} - \delta, \tag{1}$$

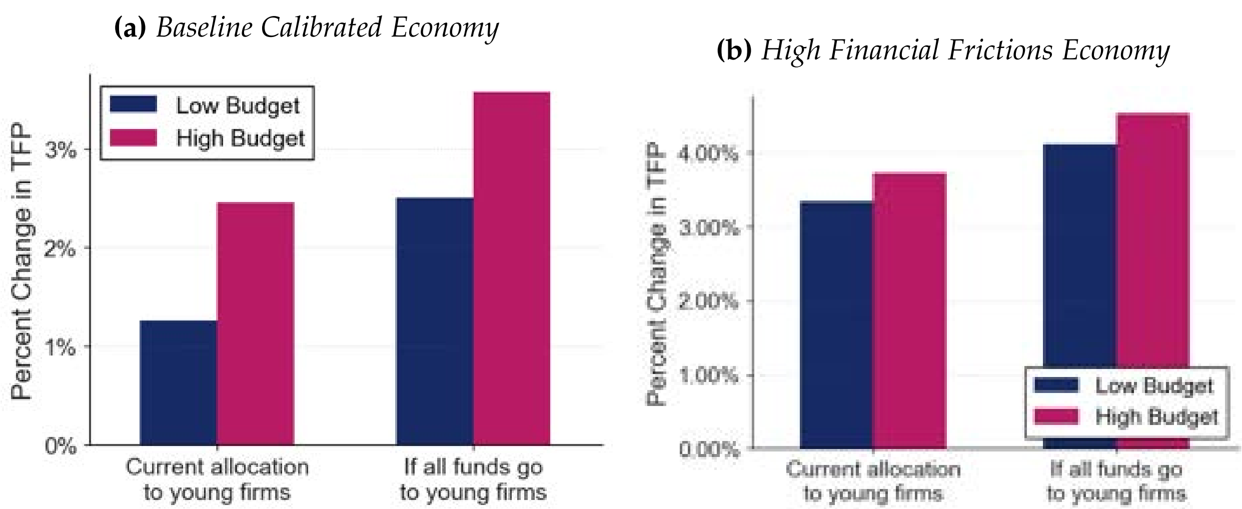
$$w_t = (1-\alpha) Z_t Z_{ct} \left(\frac{K_{ct}}{L_{ct}} \right)^{\alpha}, \tag{2}$$

These demand functions imply that we can pin down the w and r prices as a function of the $\frac{K_{ct}}{L_{ct}}$ ratio for the corporate firm. Note also that:

$$\frac{K_{ct}}{L_{ct}} = \left(\frac{\alpha Z_t Z_{ct}}{r_t + \delta} \right)^{\frac{1}{1-\alpha}}$$

Thus, following a standard trick in the literature, we can guess r, implying a $\frac{K_{ct}}{L_{ct}}$ that determines a wage w. Given these prices, we solve the heterogeneous agents policies and distributions and find the K_c that clears asset markets. We used this to iterate on r until convergence.

Figure B.1: *High financial frictions calibration: aggregate TFP impacts – Changing Spending vs Allocation of Industrial Policy via Venture Capital*



Notes: This figure shows model counterfactuals of changes in the budget for industrial policy via venture capital and changes in the allocation of funding across funds of different life cycle stage focus.

Age dependent λ We are currently running counterfactuals with a λ that is a function of the firm's age and funding history.

B.2 Additional Counterfactual

We consider an economy where borrowing frictions are higher (lower λ). We repeat the exercise done in Figure 6; the baseline results from that are repeated in Figure B.1a. In Figure B.1b, we show the results from the additional counterfactual with a lower λ.

Here we find that in markets with more difficult bank financing (lower λ), the aggregate TFP effects of industrial policy are 2.5x higher than in more developed markets, even at the baseline allocation and a low budget. Interestingly, further increasing the budget there yields lower increases than in more developed settings.

B.3 Alternative Version of the Model with Value-Based Funding Amounts

In the text, VCs fund companies according to the shortfall $F^*(z,a) = k(z) - k(a)$ left by borrowing constraints. We have experimented with other micro-foundations.

Alternatively, we present a version where VCs follow a funding rule that injects funding proportional to the expected discounted value of the (unconstrained) company, denoted by $v(z)$, which only depends on its productivity z. Since in exchange, VCs take ownership shares τ and are themselves funding constrained, the final funding amounts are given by

$$F_g(z) = \omega_g \cdot \tau \cdot v(z) \tag{3}$$

ω_g is the crucial object described in the text: the common multiplier that determines the amount received by funded firms on average. We can derive an analytical expression for $v(z)$ (where $\theta = \frac{1}{\nu}$, $\overline{\pi}(w,r) = \nu \cdot \overline{y}(w,r)$, and η_z is shape of the Pareto distribution):

$$v(z) = \frac{\overline{\pi}(w,r)}{1-\eta\beta\gamma} \cdot \left(z^\theta + \frac{\eta\beta}{1-\eta\beta} \cdot \frac{\eta_z}{\eta_z - \theta} \cdot (1-\gamma) \cdot z_{min}^\theta \right) \tag{4}$$

Intuitively, more productive firms will get a higher funded amount if they happen to become funded since the funding rule $F(z) = \omega_g \cdot \tau \cdot v(z)$ increases with z due to its effect on firm value. Absent VC funding, if a poor entrepreneur gets a good business idea, due to the borrowing constraint, their level of production will be constrained to be lower than its unconstrained level $y\,(a,z) \leq y^*\,(z)$, inducing productivity and output losses from misallocation. When allowing VCs to intermediate government funds skewed towards highly productive entrepreneurs, low-wealth yet highly productive productive entrepreneurs, when funded, can reach a level of assets that at least gets them in equal footing to compete with their wealthy counterparts that have a business idea of much lower quality.

C Additional Details on the Empirics

C.1 Merging of PitchBook & Orbis Databases

This section provides details of our approach to merging PitchBook and Orbis databases.

We merge companies from the PitchBook database with their financial statements in Orbis by matching company names across the two databases. PitchBook supplies four name variants for each firm – "company name", "legal name", "former name", and "also-known-as name" – while Orbis provides two – "native name" and "international name". Our matching algorithm considers all four PitchBook variants, but assigns higher priority to certain names at specific steps. The Orbis variants are treated equivalently. This means that each of the four PitchBook names is compared against a combined set containing both Orbis names using a fuzzy matching algorithm.

We adopt the following procedure. In the first step, we match the cleaned PitchBook and Orbis company names on a country-by-country basis using the Jaro-Winkler similarity metric, retaining all pairs with a similarity score greater than 0.95. This step often yields multiple Orbis firm identifiers for a single PitchBook entity, therefore we undertake additional screening stages to discard false positives and retain a single correct match. We employ this two-tiered approach – rather than simply choosing the pair with the highest similarity score – for three reasons.

First, we clean company names before the matching. The preprocessing removes redundant whitespace, strips legal-form suffixes (for instance, "s.r.l." for Italian firms) based on country-specific frequency tables, replaces non-ASCII characters, removes punctuation, and applies the cleaning routines provided by the cleanco Python package. Absent this cleaning, the subsequent matching algorithm would generate numerous false positives, because the two databases might store firm names in different formats. For instance, the legal-form suffix "s.r.l." may appear in only one database, causing the longer name to spuriously resemble an unrelated entry.

Second, the cleaning procedure shortens and homogenizes the strings, so two originally distinct names can collapse into an identical cleaned form. For instance, a single PitchBook firm may yield several perfect matches with different Orbis companies – that is, pairs with a Jaro-Winkler similarity of 1.

Third, because the cleaning procedure is necessarily imperfect, the correct counterpart may not always receive the highest similarity score. We therefore keep a limited set of top-scoring candidates for each PitchBook firm and postpone the removal of any remaining false positives to later stages of the algorithm.

In the second stage, we discard incorrect matches using Orbis incorporation date: any candidate in which the first deal recorded by PitchBook precedes the firm's incorporation date in Orbis is removed. In the third stage, we apply a regional consistency filter based on NUTS2 codes. Orbis directly supplies NUTS2 identifiers, whereas PitchBook provides postcodes, which we convert to NUTS3 and subsequently aggregate to NUTS2, yielding nearly complete geographic coverage. We operate at the NUTS2 rather than the more granular NUTS3 level to accommodate minor discrepancies that can arise when either database is populated.

The next step involves filtering using the company size – the number of employees reported in Orbis. Company size is also drawn from PitchBook, whose coverage, although much less comprehensive than Orbis, is available for the firms in our matched sample. For calendar years reported in both databases, we construct two measures:
$M_1 = max(employees^{PitchBook}, employees^{Orbis}) / min(employees^{PitchBook}, employees^{Orbis})$ and
$M_2 = max(employees^{PitchBook}, employees^{Orbis}) - min(employees^{PitchBook}, employees^{Orbis})$.
We drop any candidate for which $M_1 > 3$ & $M_2 > 5$ at any point in time.

At the next stage, we drop all candidate matches, where the website address in Pitchbook and Orbis don't match, leaving the entries where the website address is missing in one of the databases.

After that, if for a company we have matches with perfectly matched website address

- we drop all other matches. Then, for each PitchBook firm, we retain only the match with the smallest value of M_1 and then the smallest absolute difference between the PitchBook and Orbis incorporation dates. We allow for some discrepancies between PitchBook and Orbis employee counts and incorporation dates using the same logic as for NUTS2 – this discrepancy might arise due to differences in database filling routines. Additionally, at every step, we keep observations for which either database lacks the relevant information. Doing otherwise, we would disproportionally drop small firms if the data coverage in either of the databases is sparser for the small firms. After the last step, instances in which a PitchBook company still maps to multiple Orbis identifiers are extremely rare.

In such cases, we retain only the match (or matches) with the highest similarity score for each firm. In the event of ties, we break them by ranking the PitchBook name variants – legal name > company name > 'also known as' name > former name – and keeping the variant with the highest priority. If several candidates still tie, we choose the candidate with the highest similarity based on the uncleaned name strings and, among those, the Orbis identifier offering the most complete financial variables coverage. Any residual duplicates are resolved by randomly selecting one identifier. Manual inspection confirms that these residual duplicates reflect historical changes in Orbis IDs rather than distinct entities, so any of the remaining matches is acceptable.

We begin with 312,050 PitchBook-listed firms headquartered in 22 European countries. The initial name-matching procedure identifies candidate Orbis counterparts for 261,457 firms (83,8%). After all subsequent cleaning filters, our final sample contains 82,748 firms (26.5% of the original PitchBook dataset) associated with 129,701 investment deals. Firms exit the sample for one of three reasons: (1) no sufficiently close Orbis match is found; (2) the candidate match is classified as a false positive; or (3) the matched firm lacks financial information in Orbis.

C.2 Preparing Financials

We rely on the Orbis historical disk data, which requires extensive preprocessing before analysis. Adapting the data cleaning procedures of Kalemli-Ozcan et al. (2015) and Gopinath et al. (2017) , we pursue three objectives:

– Ensure temporal consistency of accounts by reconciling the different statement types available for each firm;

– Eliminate reporting errors and balance-sheet inconsistencies;

– Drop or winsorize extreme outliers to control for reporting errors and so that outliers do not distort subsequent analyses.

Our procedure departs from Kalemli-Ozcan et al. (2015) by incorporating several additional screening steps inspired by Gopinath et al. (2017) . In turn, it diverges from Gopinath et al. (2017) in two respects: we handle consolidation codes differently, and we are less aggressive in eliminating observations with missing values, because many variables later enter our difference-in-differences estimators individually.

First, we drop any observation that lacks information on all four core financial variables – total assets, revenue, sales, or number of employees. Second, we retain only those financial statements whose reporting interval is between 10 and 14 months, thereby removing filings for which the previous report occurred more than 14 months or fewer than 10 months earlier. Third, for each company-year, we keep only "last-twelve-months" reports whenever a "last-twelve-months" statement is available, eliminating unorthodox-horizon filings for the same year. Fourth, we exclude statements filed between April and August and reassign statements dated in January–March to the preceding fiscal year. This final step differs from the procedure in Kalemli-Ozcan et al. (2015) , which shifts all filings from the first six months to the prior year without removing the mid-year statements. Our modification is motivated by our heavier reliance on the longitudinal Orbis series, for which strict year-to-year consistency is essential.

Next, for each company-year, we retain only the statement (or statements) filed in the

month closest to the calendar year-end. We then exclude the entire firm if any retained observation exhibits: – negative total assets;
– negative number of employees;
– number of employees > 2 000 000;
– negative sales;
– negative tangible fixed assets.

We must also account for firms reporting both consolidated and unconsolidated accounts or the possibility that a firm's filings switch between consolidated and unconsolidated formats over its life cycle, where consolidated accounts are financial statements of a company with multiple divisions or subsidiaries. Orbis distinguishes these cases with the following consolidation codes:
– U1: Only unconsolidated accounts are available in Orbis.
– C1: Only consolidated accounts are available in Orbis.
– U2-C2: Both unconsolidated and consolidated accounts are available in Orbis.
– LF: Only limited financial information is available in Orbis (usually, only capital and number of employees).

For each firm, we calculate the number of fiscal years covered by unconsolidated accounts (codes U1 and U2) and by consolidated accounts (codes C1 and C2). We then retain only the statement type that provides the broader temporal coverage, while preserving any LF records for years not spanned by the chosen account type. When both a C1 and a C2 (or U1 and U2) accounts exist for the same year, we keep the version with the more complete set of variables – or select one at random if their coverage is identical.

This approach differs slightly from Kalemli-Ozcan et al. (2015) , who analyze consolidated and unconsolidated accounts separately, comparing the results, and from Gopinath et al. (2017) , who rely exclusively on unconsolidated data. We diverge for two reasons. First, double-counting is not a concern of our study because our sample utilizes uniquely identified PitchBook firms. Second, we remain agnostic about whether consolidated or unconsolidated statements better capture the effect of attracted investment on firm performance; resolving that question would require case-by-case examination of each deal's description and terms.

At the next stage, we test the internal consistency of each balance sheet by comparing Orbis-reported aggregates with the sums of their disclosed components. Following Gopinath et al. (2017) , we compute the seven ratios below, each expressed as the ratio of a component sum to its corresponding aggregate:

– The sum of tangible fixed assets, intangible fixed assets, and other fixed assets as a ratio of total fixed assets.

– The sum of stocks, debtors, and other current assets as a ratio of total current assets.

– The sum of fixed assets and current assets as a ratio of total assets.

– The sum of capital and other shareholder funds as a ratio of total shareholder funds.

– The sum of long-term debt and other non-current liabilities as a ratio of total non-current liabilities.

– The sum of loans, creditors, and other current liabilities as a ratio of total current liabilities.

– The sum of non-current liabilities, current liabilities, and shareholder funds as a ratio of the variable that reports the sum of shareholder funds and total liabilities.

We estimate each ratio's empirical distribution and remove firm-year observations that fall below the 0.1 percentile or above the 99.9 percentile.

We then inspect several variables that enter the subsequent analysis to identify reporting errors and extreme outliers:

– Total liabilities. We construct two alternative measures: (1) the difference between the "shareholder funds + liabilities" variable and the shareholder funds, and (2) the sum of current and non-current liabilities. We drop firm-year observations in which either measure is negative, and we eliminate firm-years whose ratio of the two measures lies outside the [0.9, 1.1] interval. Following Gopinath et al. (2017) , we retain the first measure as our definition of total liabilities.

– Negative entries. We drop any firm-year observation with negative values for current liabilities, non-current liabilities, current assets, loans, creditors, other current liabilities, long-term debt, depreciation, costs of employees, or intangible fixed assets.

– Liability composition. We remove observations in which long-term debt exceeds total liabilities by more than 1 percent.

– Net worth consistency. We compute net worth as total assets minus total liabilities and compare it with the shareholder funds variable. We drop company-year observations for which the ratio of these two variables falls outside [0.9, 1.1] interval.

– Asset composition. We drop firm-year observations in which tangible fixed assets exceed total assets.

– Capital-Labor Ratio. We drop every observation for a firm if in any year the capital to costs of employees ratio falls in the bottom 0.1 percent of the distribution. We then remove outliers – firm-year observations with ratios lying below the 0.1 or above the 99.9 percentile.

– Shareholder funds. We compute the shareholder funds to total assets ratio and drop observations in the bottom 0.1 percentile.

-- Leverage ratio. We construct two leverage ratio measures – tangible fixed assets to shareholder funds and total assets to shareholder funds – and remove outliers, dropping values below the 0.1 percentile and above the 99.9 percentile.

– Value Added. We remove firm-years with negative value added. We then calculate the costs of employees to value added ratio and drop firm-year observations in the bottom 0.1 percentile and observations with the ratio exceeding 1.1 (which is a more restrictive cutoff than dropping values in the top 99.9 percentile).

After all these filters, we winsorize every variable used in the subsequent analysis at the 1 and 99 percentiles.

C.3 Stratified Sampling and Propensity Score Matching

To assess the impact of the European Investment Fund on firm performance, we employ a difference–in–differences framework centered on the firm's first venture–capital (VC) transaction. Our matched PitchBook-–Orbis dataset yields two treated subsamples: firms that receive their initial VC financing from the European Investment Fund (EIF) and firms whose first VC backer is another investor from PitchBook. We don't want to use the latter subsample as the non–treated group, since this would mean we would completely ignore available information about the first non–EIF investment deal (this would be equivalent to just comparing the first EIF deal effect to the overall dynamics of Pitchbook-treated firms). Instead, we want to compare deal–vs–deal effects. To do that, we introduce a common non–treated sample of firms taken from the Orbis database and compare the effects of the first EIF and non–EIF investment deals separately against this common non–treated sample.

To satisfy the parallel trends assumption, we need all three subsamples (EIF–treated, PitchBook–treated, and never–treated firms from Orbis) to show similar dynamics prior to the moment of the first VC investment. We ensure this by constructing a control sample of firms that are similar to the treated companies during the three–year window preceding the deal. At the same time, we want to be able to generalize conclusions drawn from difference–in–differences analysis to all EIF VC investments, which means that we want to preserve the size of EIF–treated subsample as much as possible in the process.

Our control group construction proceeds in two stages:
1) EIF–PitchBook matching. We select PitchBook firms that have never received EIF financing, but have received investment deals elsewhere, matching them to EIF–backed firms on pre–investment characteristics.
2) Orbis–based augmentation. We draw a control sample from Orbis, matching it to the combined set of EIF– and non–EIF VC–backed PitchBook firms obtained in stage 1.

Using this two–tiered control group, we estimate treatment effects separately for (i) EIF–backed firms relative to the Orbis control sample and (ii) non–EIF VC–backed firms relative to the same Orbis controls.

The first step enables a deal–to–deal comparison, as the date of the initial investment is observed for both EIF-backed firms and PitchBook firms financed by other investors. The second stage, in contrast, compares the impact of the first EIF or PitchBook deal with the overall performance trajectory of matched Orbis firms; here, the investment date cannot be used in the matching algorithm, as it is unobserved for the control Orbis firms. A comparison restricted to EIF– and PitchBook–backed firms would shed little light on how treated firms perform relative to the representative enterprise in the economy – PitchBook covers only firms capable of attracting outside investment – this is another rationale for including Orbis firms as a common control sample.

Within each of the main steps, we follow a two–stage procedure. First, we construct a pool of potential controls through stratified sampling that reproduces the distribution of key non-financial characteristics of treated firms. Second, we apply Propensity Score Matching (PSM) to draw the final control observations from this pool, using financials from the three–year window preceding the deal.

For the stratified sampling, we employ two closely related designs for EIF–PitchBook and (EIF+PitchBook)–Orbis matches. For the former, we create strata along country, firm size (0-9, 10-49, 50-250 and 250+ employees), macro sector in CompNet, and first deal 5-year strata dimensions. For the latter, we create strata along country, firm size (0-9, 10-49, 50-250 and 250+ employees), macro sector in CompNet, first deal 5-year strata dimensions (matching the deal year in the treated sample to the year observations in the non-treated sample), and 5-year company age cohort. For every treated firm we randomly sample non-treated companies from the same stratum, targeting a control-to-treated ratio of 6:1 for EIF–PitchBook match on the first stage and 60:1 ratio for much bigger sample of Orbis firms in the second (EIF+PitchBook)–Orbis stage. To do this, we match 'first deal year – company' observations for EIF–PitchBook match in the first stage. Whereas in the (EIF+PitchBook)—Orbis stage, the treated ’first deal year – company’ observation is matched to any calendar-year record of an Orbis control firm, because deal-date information is unavailable for the latter.

In the second stage we apply Propensity Score Matching (PSM), a statistical technique used to reduce selection bias by equating groups based on observed covariates. Each firm’s probability of receiving EIF financing is estimated with a probit model that conditions on observable characteristics measured three years before the first EIF VC deal. Treated firms are then paired with control firms displaying similar propensity scores, ensuring comparability on the observed covariates. The procedure follows the approach used in other evaluations of EU investment programmes [cite impact assessment memos by the EIB and EIF] and is implemented with the psmatch2 module in Stata. We follow the logic of the stratified sampling step – we match ’first deal year – company’ observations for EIF–PitchBook match on the first stage. Whereas in the (EIF+PitchBook)—Orbis stage, the treated ’first deal year – company’ observation is matched to any calendar-year record of an Orbis control firm.

Including three-year lags among the covariates not only enhances comparability but also helps satisfy the parallel-trends assumption underpinning our stacked difference-in-differences design. The PSM model conditions on asset ratio, number of employees, total assets, revenue growth, employment growth, asset turnover ratio, cash ratio, leverage ratio, and current ratio. It also incorporates quadratic and cubic terms of these variables, indicators for missing observations in financial variables, and fixed effects for firm size, country, company age 5-year cohort, 5-year cohort, and macro sector in CompNet. Propensity scores derived from this specification are used to select a control cohort equal in size to the treated group. Match quality is evaluated below: Figure 1 compares the pre- and post-match distributions of the key covariates and reports balance diagnostics, whereas Figures 2 and 3 display the propensity-score distributions for treated and control observations before and after matching.

We aim to retain as many EIF-backed firms as possible. By following our stratified sampling and PSM routine, we succeed in matching 87.9% of feasible EIF-treated firms in the sample to suitable PitchBook and Orbis counterparts.

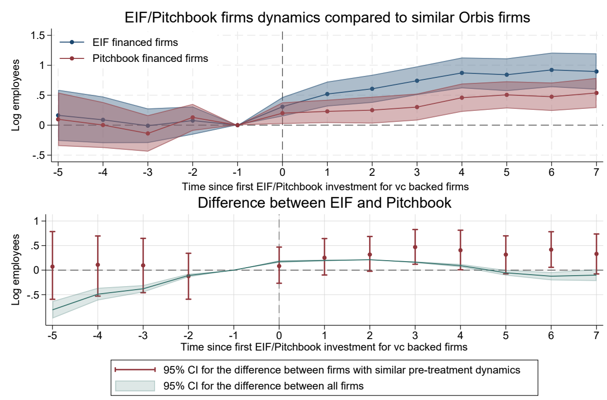
After constructing the control sample, we use stacked difference–in–differences approach to estimate the effects of the EIF investment, following Wing, Freedman, and Hollingsworth (2024) and Cengiz et al. (2019). EIF-treated deals in our sample appear from 1998 to 2022 and the dataset is unevenly populated across years. Additionaly, we don't expect investment deal effect to be homogeneous across time. That is why the main concern of the chosen difference–in–differences approach is that we can estimate dynamic treatment effects rather than compositional changes, ensuring the absence of pre–trends. Stacked difference–in–differences design of Wing, Freedman, and Hollingsworth (2024) allows us to do exactly that. We ensure compositional balance by investigating the effects of only deals for which we observe full 7-year post treatment and 5 year pre-treatment window among the control sample of firms in Orbis.

Further details will be provided in future version of this Appendix.

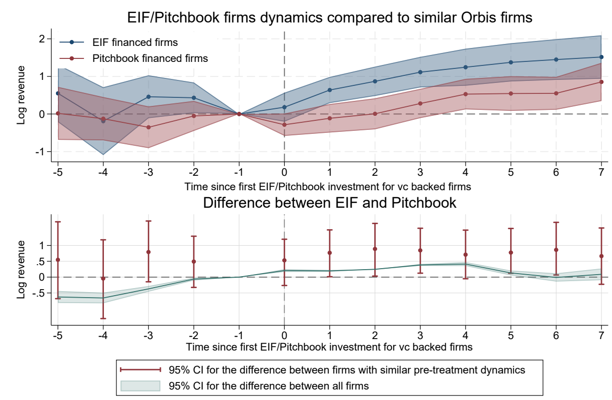
Additional dynamic regression estimates We present several additional facts about the post-investment firm dynamics in Figure C.1. First we show that results broadly hold beyond employment using alternative measures of firm performance. Further, we show that the effects for firms invested on by VCs with the EIF as an LP are not worse (if anything, a little better) than those invested on by VCs in PitchBook without the EIF as an LP (when compared against all Orbis firms as a control group). We view this as potentially consistent with the notion that EIF-linked funds are able to deploy larger amounts of cash per firm, lifting financing constraints more. However, we are exploring alternative stories such as positive signaling, the opening of doors to guarantees or debt after EIF-linked VC investments, and selection.

C.4 EIC results: To Be Added

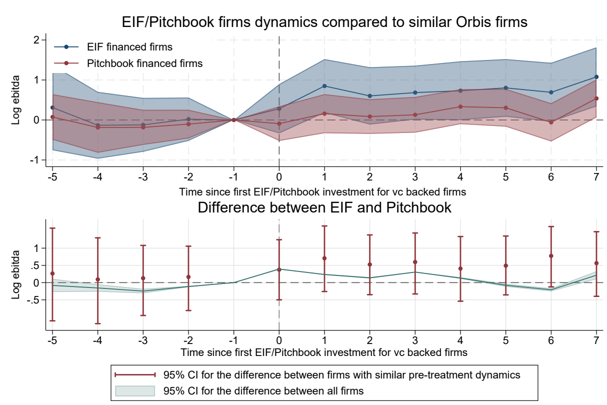
Figure C.1: *Post VC Investment Dynamics*



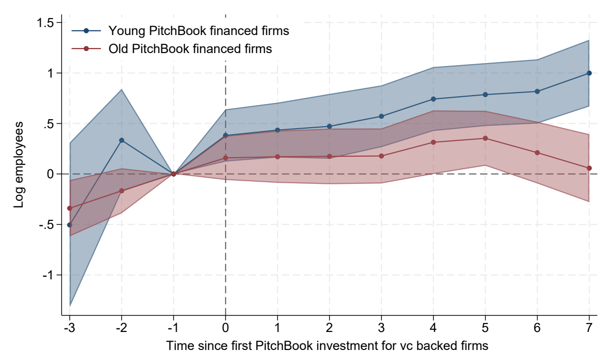
(a) *EIF v.s. non-EIF in PitchBook Employment*



(b) *EIF v.s. non-EIF in PitchBook Revenue*



(c) *EBITDA*



(d) *Young vs Old PitchBook non-EIF*

Notes: This figure shows a stacked diff-in-diff run separately for EIF and private VC invested firms using longitudinal data from Orbis using different outcome measures (e.g. revenue) and comparison groups (comparing EIF-linked only and all non-EIF VC investments in PitchBook against Orbis controls).