Startup Types and Macroeconomic Performance in Europe*

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Abstract

We construct a new and comprehensive data set on 1.3 million European startups. A cluster analysis identifies five distinct startup types that are consistently present across countries, industries, and cohorts. The initial differences between these startup types are persistent and each type displays a characteristic life cycle in terms of productivity, employment, and survival. An agnostic firm dynamics model helps quantify how much structural policy could improve macroeconomic performance by shifting the composition of startup cohorts. We show that policies benefiting high-performance startups, while discouraging the entry of underperforming firms, can yield substantial gains in aggregate employment and productivity.

JEL classification: D22; D24; G32; L11; L25; L26; O47

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1 Introduction

In many advanced economies, politicians are increasingly concerned about lackluster macroeconomic performance as reflected in anaemic productivity growth and, in some countries, low employment levels (OECD, 2015; Syverson, 2017; Akcigit and Ates, 2021). Naturally, policymakers are looking for novel levers to structurally improve these macroeconomic outcomes. A long-standing literature has explored several directions that policy can take, including tax measures to stimulate R&D and innovation (Bloom, Griffith and Van Reenen, 2002; Akcigit, Hanley and Stantcheva, 2022b) and structural reforms to reduce distortions in labor markets (Hopenhayn and Rogerson, 1993), financial markets (Buera and Shin, 2017) and product markets (Edmond, Midrigan and Xu, 2021). Such policies typically aim to either improve the productivity of existing firms or to strengthen the Darwinian selection process that weeds out inefficient enterprises (Syverson, 2011). This paper investigates an entirely different policy lever, one that has remained largely unexplored: influencing the types of new firms that are being founded.

The idea of improving the composition of new firm cohorts—as opposed to "fixing" established generations—appears attractive for two reasons. First, startups are key drivers of job creation and productivity growth (Foster, Haltiwanger and Krizan, 2001; Haltiwanger, Jarmin and Miranda, 2013; Adelino, Ma and Robinson, 2017). Recent evidence (referenced below) furthermore suggests that ex ante heterogeneity among newly established firms helps to predict their performance later in life. It follows that structural policies that successfully shift the types of startups that enter the economy, may generate substantial macroeconomic gains. Second, forward-looking policies to shift the composition of startup cohorts also appear attractive because the rates of firm entry and exit are high, typically around 10 percent annually. This means the majority of firms that will be active twenty years from now are yet to be founded, while many current firms will no longer exist by then.[1]

[1] For instance, the US Longitudinal Business Database (LBD) shows that, in 2019, 71 percent of all firms were 20 years old or younger. The startup rate in that year was 8.2 percent. In the appendix, we show that European startup rates are comparable. Dent, Karahan, Pugsley and Şahin (2016) use the LBD to show

Some governments have already begun to focus policies on specific startup types. For example, in May 2020, the UK government launched a Future Fund to support the "most innovative businesses" and "top-performing startups with huge economic potential" that will "create high-skilled jobs".[2] Yet, in practice, government policy often lacks empirical guidance on how to effectively stimulate entrepreneurship. As a result, many efforts to do so fail (Lerner, 2009). These observations raise important questions: Can targeted startup policies structurally improve macroeconomic performance by altering the mix of startup types? And, if sizeable gains are possible, what kinds of startups should be encouraged and how to identify these types? At present, there is no clear answer to these questions.

We tackle these questions using large-scale administrative data sets for ten European countries: Croatia, Denmark, Finland, France, Italy, Lithuania, the Netherlands, Slovenia, Spain, and Sweden. The data contain a rich set of variables, derived from the balance sheets and income statements of individual startups. We collected these data in close collaboration with the Competitiveness Research Network (CompNet), which uses a distributed micro-data approach to generate regularly updated, micro-based, and internationally harmonized data on European firms.

Our data provide unique cross-country panel observations on more than 1.3 million European startups, thus achieving representative coverage of the full startup population. This allows us to draw a direct link between micro and macro outcomes along various key dimensions. Our data are particularly useful in comparison with data sets slanted towards larger firms (such as Compustat); surveys following just one startup cohort (such as the Kaufman Firm Survey); administrative data covering only a limited number of variables (such as the US Longitudinal Business Database); and databases that poorly capture firm entry and exit

that about half of all sectoral employment reallocation in the US since the end of the 1980s reflects changes in startup employment (that is, the entry margin) rather than employment shifts among incumbent firms.

[2] https://www.gov.uk/government/news/uk-tech-firms-and-investors-brought-together-for-landmark-treasury-conference. Similarly, the recent Inflation Reduction Act in the United States expands the availability of R&D tax credits to pre-revenue innovative startups, see https://www.whitehouse.gov/briefing-room/statements-releases/2022/09/12/fact-sheet-how-the-inflation-reduction-act-will-help-small-businesses/.

(such as Orbis, cf. Bajgar, Berlingieri, Calligaris, Criscuolo and Timmis (2020)).

Our analysis of these novel data is guided by a theoretical firm dynamics framework in the tradition of Hopenhayn (1992). This model can be used in a tractable way to study how policies affect the composition of startup types and thereby macroeconomic outcomes. It turns out we can conduct these policy counterfactuals while remaining largely agnostic about the demand and production structure of firms. Only three sets of empirical statistics are required. The first set consists of multidimensional life-cycle profiles of the various startup types. The second set of statistics contains entry elasticities with respect to (the net present value of) profits. The third is the immediate impact of a policy instrument on firm profits. Importantly, all of these statistics can be readily estimated using our data set.

A key question we face is how to classify startups into types, given that these types are not directly observed. We address this issue by using K-means clustering, an unsupervised machine learning algorithm that has recently gained popularity in the applied economics literature as a way of dealing with latent heterogeneity. Underlying our application of this method is the idea that a startup's type is revealed by a number of key choices entrepreneurs make when commencing operations. Exploiting the richness of our data, we classify startups based on five important choice variables in the initial year of operation: employment; the capital-to-labor ratio; total assets; the leverage ratio; and the cash-to-assets ratio. The practical advantage of this approach is that these variables are easily observed from tax information at the very beginning of a firm's life cycle. They can therefore readily be used to differentiate startups and to facilitate targeted policies.

The clustering algorithm endogenously groups startups into five types. It turns out that this classification captures the majority of the empirical variation in the clustering variables. Moreover, the outcome of the clustering analysis is remarkably robust across countries. In each country, we obtain the following five startup clusters: large; capital-intensive; high-leverage; cash-intensive; and basic. Using a "meta-clustering" analysis, we verify that each of these types has similar characteristics across countries. Moreover, we use Monte Carlo simulations to check that this similarity across countries is not due to mechanical factors related, for example, to the shape of the distribution of the clustering variables.

We next show that the distribution of startups across the five types is quite stable across countries, economic sectors, and cohorts. Finally, we track these five startup types for more than a decade and document their life-cycle profiles in terms of the main choice variables. We find that the initial cross-type differences are persistent. All of these findings confirm that the clustering algorithm robustly captures fundamentally different firm types.

Based on the clustering outcomes, we then document heterogeneity in performance. We find large and persistent differences in employment and productivity across the various types. This implies that a change in the composition of startups can potentially have large macroeconomic effects. A number of salient patterns emerge. In particular, the performance of the high-leverage startup type tends to be consistently poor. Even when we compare startups within the same country and economic sector, the cluster of highly leveraged firms displays substantially lower labor productivity and total factor productivity (TFP). These firms are also significantly more likely to exit in any given year. By contrast, startups that stand out because of their capital-intensive production technology, their high level of employment and productive assets, or their high cash-to-assets ratio, typically boast higher productivity levels and lower exit probabilities.

Having documented these structural and persistent differences between startup types, we use our model to conduct a number of counterfactual exercises to quantify the "policy space" for improving macroeconomic performance via the startup composition channel. Concretely, we consider a budget-neutral differentiation of corporate income tax rates by startup type. This tax differentiation alters the incentives for different firm types to enter the economy and thus affects the startup mix itself. While this particular policy suits us because of its simplicity, our framework can be readily applied to many other structural policies.

We proceed to compute the effects of such budget-neutral tax reforms on the macro economy and find that they can significantly increase aggregate productivity and/or employment by tilting the mix of startup types. For example, a large but budget-neutral tax reform that modifies tax rates by a maximum of 20 percentage points at the firm level, can increase aggregate productivity (employment) by as much as 4.5 percent (11 percent). These results suggest that targeted startup policies can be highly cost-effective compared to measures that affect startups uniformly. Note that targeting can be achieved either by explicitly conditioning on firm types or by exploiting that different startup types are exposed differentially to existing policies. For example, a more favourable tax regime for the expensing of capital investments would disproportionately benefit capital-intensive startups, thus shifting the startup composition towards this type.

Our counterfactual exercises show that the largest productivity gains can be reaped by reducing taxes for capital-intensive, large, and cash-intensive startup types while financing this measure by an increase in taxes for basic and high-leverage types. To increase employment by the maximum amount, taxes are to be cut for large and high-leverage types but increased for cash-intensive startups in particular.

Stimulating large and capital-intensive startups also appears attractive from a broader welfare perspective, as we show that these firms tend to pass gains from their high productivity levels on to workers, in the form of higher wages, as well as to consumers, in the form of modest profit margins (in particular the large types). Finally, we use our results to shed light on existing policies—including size-dependent corporate taxes and measures that influence startups' financial structure—and their effects on the startup composition.

Related literature

We build on an emerging literature that documents the importance of ex ante heterogeneity for firms' performance over their life cycle. This heterogeneity manifests itself in vastly different growth expectations among new entrepreneurs (Hurst and Pugsley, 2011), predictability of firm performance based on observable characteristics of entrepreneurs and businesses at the moment of startup (Schoar, 2010; Guzman and Stern, 2015; Belenzon, Chatterji and

Daley, 2017; Guzman and Li, 2022) as well as strong cohort effects over the business cycle (Sedláček and Sterk, 2017). Quantitatively, ex ante heterogeneity accounts for the majority of variation in firm-level employment, as shown by Sterk ⓡ Sedláček ⓡ Pugsley (2021), who estimate an employment process using micro data.

We contribute to this literature in four important ways. First and foremost, we are the first to analyze how policy can be designed to exploit ex ante firm heterogeneity to improve macroeconomic outcomes. Second, we treat ex ante heterogeneity explicitly as a multidimensional object. Most existing studies focus on just one dimension of heterogeneity, such as firm size.[3] We instead jointly characterize firms by five key choice variables at startup and consider several performance measures (labor productivity, TFP, profitability, and exit probability). Third, the quality of our data enables micro-to-macro mapping along these dimensions and a comparison of this mapping across countries. This allows us to paint a rich and novel characterization of the European startup landscape. Fourth, the clustering algorithm classifies firms into types based on observables in the first year of operation. This makes our approach straightforward to implement by policymakers. By contrast, other studies have not made firm types observable (Albert and Caggese, 2021; Sterk ⓡ al., 2021).

Another key contribution of this paper is that we obtain empirical estimates for the elasticity of firm entry and can show that these elasticities are heterogeneous across firm types. Such estimates are relatively rare in the literature, even though they are a standard input in firm dynamics models, which often assume either fixed entry (that is, a zero elasticity) or a free entry condition (that is, an infinite entry elasticity).[4] Our estimates can thus be used to impose more empirical discipline on models in the tradition of Hopenhayn (1992) and models with firm entry more generally.

[3]Recently, Bernard, Dhyne, Magerman, Manova and Moxnes (2022), using Belgian data on firm-to-firm trade, have underlined the importance of multiple attributes to explain firm-level success and, therefore, dispersion in the firm-size distribution. Other work assesses the role of specific ex ante differences across startup founders, such as their business experience (Lafontaine and Shaw, 2016), cognitive and non-cognitive personality traits (Levine and Rubinstein, 2017), and age (Azoulay, Jones, Kim and Miranda, 2020).

[4]Other estimates can be found in Sedláček and Sterk (2017) and Gutiérrez, Jones and Philippon (2022). They rely, however, on full-blown structural DSGE models to estimate the entry elasticity, whereas our method is agnostic. Moreover, we estimate elasticities for different startup types.

Moreover, we add to the literature on the micro origins of aggregate productivity (Hsieh and Klenow, 2009; Restuccia and Rogerson, 2013; Hsieh and Klenow, 2014; Midrigan and Xu, 2014; Moll, 2014; Gopinath, Kalemli-Özcan, Karabarbounis and Villegas-Sanchez, 2017; Brandt, Kambourov and Storesletten, 2020). Here, our focus on startup types and their persistent performance differences provides a new perspective on productivity dispersion between firms (De Loecker and Syverson, 2022). It also opens up a new avenue to better understanding the drivers of differences in aggregate productivity across countries and industries, as well as changes over time. Instead of focusing on the "startup deficit"—a decline in firm entry observed in several countries over the past decades (Decker, Haltiwanger, Jarmin and Miranda, 2017; Alon, Berger, Dent and Pugsley, 2018; Karahan, Pugsley and Şahin, 2019)—we highlight the importance of the *composition* of new startup cohorts for aggregate productivity and employment.

Finally, our results complement studies that investigate the effectiveness of interventions to improve firms' performance *after* they have been established, such as consultancy services and management training (Bloom, Eifert, Mahajan, McKenzie and Roberts, 2013; Iacovone, Maloney and McKenzie, 2022) and business accelerators (González-Uribe and Leatherbee, 2018; González-Uribe and Reyes, 2021). By contrast, we explore how aggregate productivity can benefit from policies that influence the composition of new startup cohorts at inception.

2 Theoretical framework

This section presents our theoretical framework on which we base the policy counterfactuals presented in Section 5.2. It also offers guidance on which empirical statistics are required to answer the questions at hand.

2.1 The model

Our theoretical framework is a generalization of the firm dynamics model of Hopenhayn (1992). It allows for endogenous entry and exit of firms as well as firm-level idiosyncratic shocks and ex ante heterogeneity. We now describe this framework in more detail.

Incumbent firms. There is an endogenous mass of heterogeneous firms. Let x be a vector of firm-level choices, such as its price and capital and labor inputs, and let z be a vector of variables that are exogenous to the firm, such as aggregate prices, productivity shocks, and policies. An individual firm, indexed by i, operates a production function given by $f_i(x, z)$. We do not take a stance on the functional form of the production function, which may include fixed costs. Moreover, we allow the production function to be firm-specific—it may, for instance, depend on the firm's type, and it may even vary with the age of the firm.

The firm also faces a demand curve $q_i(x, z)$ that depends on its price and potentially on other choice variables included in x (for example, the firm might expand its demand via advertising, a form of intangible capital accumulation) as well as shocks (for example, z could include demand shocks). Again, we do not take a stance on the details of the demand structure and we allow it to be firm-specific. For example, it may depend on the firm's type. Finally, we allow for an arbitrary set of constraints, which may also be firm-specific.

Time is discrete and indexed by t. There is a finite number of ex ante firm types, indexed by j. A "type" refers to a set of commonalities in demand and production structures, as well as constraints, among a group of firms. Yet we also allow for heterogeneity within startup types reflecting firm-level shocks or initial conditions.

The firm sets its choice variables in order to maximize, at any point in time and given its constraints, the expected value of profits. The firm value is thus given by:

$$V_i = \max E \sum_{t=0}^{\infty} \Lambda^t \pi_i(x_{i,t}, z_{i,t})$$

where E is the expectations operator, Λ is the firm's discount factor, which, for simplicity, we assume to be common across firms, and $\pi(\cdot)$ is the profit function implied by $f(\cdot)$ and $q(\cdot)$. A firm exits (forever) if and only if the firm no longer has positive value, that is if and only if $V_i < 0$.[5]

Entrants. For any type j, there are a certain number of potential entrants in any given period. Potential entrants do not yet know their precise startup fundamentals, such as their production function, demand function, and initial conditions. However, they do know their type and the distribution of fundamentals within their type.

Each potential entrant then faces an entry decision. If they decide to enter, they must pay an entry cost θ_i which depends on the firm's type as well as the individual potential entrant. After paying the entry cost, the entrant learns its startup fundamentals. Subsequently, the firm may be hit by shocks, for instance to its productivity or demand.

Let $\mathbb{E}_j V$ be the *ex ante* expected value of a firm of type j, that is, before paying the entry cost and before learning the startup fundamentals. Optimal decision-making implies that a firm of type j is started whenever $\mathbb{E}_j V \geq \theta_i$. That is, there exists a cutoff value of θ_i such that only potential entrants with an entry cost below the cutoff actually start a firm.[6]

We can now express the actual number of entrants of type j as $n_j = g(\mathbb{E}_j V, \Gamma_j)$ where g is an increasing function in $\mathbb{E}_j V$, and where Γ_j denotes the number of potential entrants of type j and their distribution over entry costs. Thus, the number of entrants is a function of the expected firm value and shocks to the number of potential entrants. Taking a first-order approximation (in logs) of this function gives the following expression for the percentage

[5] This condition could be relaxed, since our subsequent analysis will not rely on it. For instance, one could introduce exogenous exit without changing the results.

[6] *Within* a type, all entrants have the same expectations prior to drawing the demand and production function. This implies there are no entry selection effects within types (only across types). While this modeling assumption is standard in the literature following Hopenhayn (1992), we verify it empirically in Section 5.2.3.

change in the number of entrants of type j:

$$d \ln n_j = \varepsilon_j \cdot d \ln \mathbb{E}_j V + \gamma_j \tag{1}$$

Here, $\varepsilon_j > 0$, is the elasticity of the number of entrants of type j with respect to the ex ante expected firm value, which is given by the mass of entrants at the entry cutoff, relative to the mass of entrants below the cutoff. Moreover, γ_j denotes shocks to the number and distribution of potential entrants of type j (that is, shocks to Γ_j). Thus, the number of entrants of a certain type may increase either because of an increase in the expected firm value, or because of a shock to the number of potential entrants and/or their distribution over entry costs.[7]

Equilibrium and aggregation. All countries in our empirical application are members of the European Union, and therefore their markets for goods, labor, and firm ownership are integrated. Accordingly, we assume that prices and wages are taken as given for any individual country (below we will relax this assumption). We can compute any aggregate variable Y as:

$$Y = \sum_a \sum_j \omega_{a,j} y_{a,j},$$

where $y_{a,j}$ is the aggregate among firms of age a and type j, and $\omega_{a,j}$ is the appropriate weighting factor (for example, the firm or employment share). Both variables can be observed directly in the data, given a classification of firm types. For instance, if Y denotes aggregate labor productivity, then $y_{a,j}$ is aggregate labor productivity among firms of age a and type j, and $\omega_{a,j}$ is the employment share of these firms.[8]

[7] An alternative setup to arrive at the same result is to assume an unlimited number of entrants and to assume that the entry cost is homogeneous across entrants, but an increasing function of the number of entrants (within a type). In that case, the elasticity ε_j is determined by the shape of the entry-cost function. See, for example, Gutiérrez et al. (2022).

[8] In turn, $y_{a,j}$ is measured in the micro data as the employment-weighted average labor productivity of individual firms.

2.2 Effects of a policy change on startup composition

Based on the above framework, we now present a simple formula to compute the effects of a change in taxes or subsidies on the distribution of startups. Let $d\mathbb{E}_jT$ denote the direct effect of a policy change on the present value of the profits of an individual firm, averaged across firms within type j. For instance, $-d\mathbb{E}_jT$ could be the increase in the present-value tax bill following an increase in tax rates. While the number and distribution of potential startups is not directly affected by the policy, startup activity will be affected through the change in firm values. Applying Equation (1), the change in the number of startups of type j due to the policy change (again, to a first-order approximation) is therefore given by:

$$d\ln n_j = \varepsilon_j \cdot [\ln(\mathbb{E}_jV + d\mathbb{E}_jT) - \ln \mathbb{E}_jV] = \varepsilon_j \cdot \frac{d\mathbb{E}_jT}{\mathbb{E}_jV} \tag{2}$$

The formula states that the change in the number of startups of type j is the product of the entry elasticity and the percentage change in the firm value as a result of the policy change. Changes in startup composition can thus be evaluated based on this formula. Intuitively, the effects of a policy on the startup composition depends on how much the startup values of different types are affected by a policy change, and on how sensitive firm entry by the various types is to changes in firm values.

In case the policy is a corporate income tax, so that tax payments are proportional to profits, $\frac{d\mathbb{E}_jT}{\mathbb{E}_jV}$ equals the change in the tax rate. More generally, $\frac{d\mathbb{E}_jT}{\mathbb{E}_jV}$ is straightforward to compute in terms of firms' profits, provided one has data on the exposure of different firm types to the policy. We will use our data to estimate the entry elasticities (Section 5.1).

Having evaluated the formula for a given policy change, we can compute the counterfactual firm and employment shares of the different types in the incoming cohort, and thus the change in the weights $\omega_{a,j}$. This in turn allows us to calculate the counterfactual level of Y, which isolates the macro implications of the compositional effects of the policy change.

In conclusion, in order to compute the effects of a policy change on startup composition, and its aggregate implications, we require three sets of statistics for each startup type: (i) life-cycle profiles for the variables of interest (for example, productivity) and the weighting factor (such as firm shares or employment shares); (ii) the elasticities of entry with respect to the firm value; (iii) the direct effect of the policy change on firm values. All can be measured in our data. However, in order to compute these statistics, we also need a method to classify firms into distinct types. We discuss our approach to this in Section 3.3.

2.3 Effects on post-entry behavior

To evaluate the formula in Equation (1), we do not need to consider the effects of the policy change on the post-entry behavior of firms. This follows immediately from the Envelope Theorem, which implies that up to a first-order approximation any such effects on the firm's value equal zero. This property makes the formula particularly convenient to apply in practice when evaluating the compositional implications of any policy change.

That said, tax changes do, of course, influence the post-entry behavior of firms, and therefore have macroeconomic effects through channels other than that of the startup composition. These channels depend on the specifics of the policy. For example, a large literature has studied how various kinds of taxes and subsidies affect firm-level and, ultimately, macroeconomic outcomes.[9] Such studies provide useful guidance to policymakers and researchers as to which macroeconomic effects tax-specific reforms may have. Our composition formula is complementary to this literature. Indeed, to evaluate the overall macroeconomic effects of a proposed tax reform, one can simply add the outcomes of our composition calculation to those from existing studies on post-entry behavior.[10]

[9] See, for example, Akcigit et al. (2022b); Zwick and Mahon (2017); Akcigit, Grigsby, Nicholas and Stantcheva (2022a); Liu and Mao (2019); Benzarti and Harju (2021).

[10] In our concrete policy application in Section 5, we consider a corporate income tax, which does not necessarily have any direct effect on post-entry behavior. Intuitively, when the government takes a certain share of firm profits, via a corporate income tax, the profit maximization problem itself remains unchanged. See, for example, Sedláček and Sterk (2019).

2.4 Welfare effects

At the margin, a change in startup composition has no effects on the welfare of entrepreneurs. To appreciate this point, note that, to the marginal entrant at the cutoff, the expected value of starting a firm exactly equals the entry cost. In other words, the marginal entrant is indifferent between entering and not entering. Yet, there may well be welfare effects that go beyond this. For instance, there are likely externalities for other stakeholders, such as workers, consumers, or the taxpayer. Quantifying these effects requires the full specification of a model, including assumptions on market structures, frictions, and preferences. Rather than taking that route, we conduct a positive analysis that focuses on macroeconomic quantities instead of welfare. Yet, we will consider a wide range of outcomes, including profits and wages, to obtain a sense of the broader welfare effects.

2.5 Equilibrium effects

So far, we have abstracted from equilibrium effects. Arguably, this is appropriate when analyzing policy changes in individual countries that are part of a large economic union such as the EU. Yet one may also consider a policy jointly implemented by all countries simultaneously. In that case, there may be equilibrium feedback effects. We now extend our framework to incorporate such effects.

The margin of equilibrium adjustment we consider is the labor market, as wages are a main component of firm costs, and we will later study aggregate employment effects. Nonetheless, the analysis can be extended to account for equilibrium effects in other markets along the same lines. Let w denote the real wage per worker, which adjusts to clear the labor market.[11] Equation (1) then extends to:

$$d \ln n_j = \varepsilon_j \frac{d\mathbb{E}_j T}{\mathbb{E}_j V} + \varepsilon_j \gamma_j d \ln w. \tag{3}$$

[11] Equivalently, we could fix goods prices and let nominal wages adjust, or fix nominal wages and let goods prices adjust.

The second term on the right-hand side captures the effect of a change in the wage on the number of startups of type j, where γ_j is the elasticity of the expected firm value with respect to w. This elasticity is equal to the present value of wage payments relative to the present value of profits.

We assume that labor supply is a function of the wage: $L^{supply} = L^{supply}(w)$.[12] Taking logs and differentiating, we obtain $dL^{supply} = \kappa \cdot dw$, where κ is the Frisch elasticity implied by the labor supply function. Given a certain change in the policy T and the wage w, we can now evaluate the new number of firms of each type, and aggregate to compute the change in total labor demand. Labor market clearing implies:

$$dL^{demand} = dL^{supply} = \kappa \cdot dw. \tag{4}$$

3 Data and clustering

Having presented the model and the implied set of sufficient statistics to analyze the compositional effects of policies, we now turn to our data and measurement.

3.1 The CompNet database

We carry out a cross-country analysis of startups based on confidential administrative micro-level sources at the national level. These data were collected in close collaboration with CompNet, a research network founded in 2012 by the European Central Bank and currently hosted by the Halle Institute for Economic Research. CompNet provides its members and external researchers with a regularly updated, micro-based, and internationally harmonized competitiveness data set for 20 European countries. To preserve confidentiality at the level of individual firms, and to improve cross-country comparisons, CompNet uses a "distributed micro-data approach" as developed by Bartelsman, Haltiwanger and Scarpetta (2004). This

[12] The labor supply schedule can be micro-founded explicitly with Greenwood-Hercowitz-Huffman preferences.

means data get annually updated by sending standardized code to national statistical agencies and central banks. These organizations then run this code on the confidential firm-level data they maintain and aggregate it up to the sector-year level in a standardized fashion. The data are subsequently returned to CompNet with key statistical moments that describe the distribution of a large number of firm characteristics at the sector-year level for each country.[13] The data set contains information about all firms in all private non-financial industries. Particular care is taken to ensure a high level of cross-country consistency to allow for international comparisons and the identification of idiosyncratic country effects (CompNet, 2018).

3.2 Startups in the CompNet database

To collect harmonized cross-country data on European startups, we embedded additional code in the standard instructions sent to national authorities in early 2021 in preparation for the eighth CompNet vintage.[14] Our code extracted data on all firms that commence their operations in a particular country and year (that is, a startup cohort). We thus define the start year as the year in which a firm is first economically active. We also observe each firm's formal registration year and drop observations if one or several of the following conditions hold: the lag between firm registration and actual startup is more than four years; registration occurs *after* the actual start year (this only happens in a handful of cases); the firm has more than 50 employees at the time of startup.[15] Once a firm enters our data set, we can track it for several years. This allows us to construct comparable data on how firms develop in terms of their employment generation, productivity, and survival—all areas on which cross-country evidence remains scant.

[13]See Lopez-Garcia and di Mauro (2015) for more details on the CompNet project.

[14]We cannot use data for Germany, Poland, and the Slovak Republic as the national data sources exclude firms with fewer than 20 employees (10 in the case of Poland).

[15]Bayard, Dinlersoz, Dunne, Haltiwanger, Miranda and Stevens (2018) match new Employer Identification Numbers with employer records in the US business register. They define firm startup (firm age is zero) as the time the first payroll is observed in the Longitudinal Business Database. While recent applications account for the bulk of firm inceptions within a year, there is a long tail of startups that begin operations only several quarters after initial registration.

This approach results in a unique cross-country and cross-sector panel of all startups established during the calendar years 2000–2019. Table A1 presents the coverage per country.[16] The panel contains information on a total of 1,345,489 startups. We aggregate the data in each country and year at either the macro (economy-wide) level or at the one-digit NACE Rev.2 industry level.[17] For each country-industry-year-cohort cell, our data set contains various firm characteristics, including average number of employees, average capital intensity, average cash ratio, average leverage ratio, as well as several productivity metrics.[18] Table A2 provides a detailed description of the main variables. All monetary variables are PPP-adjusted and real variables are deflated with sectoral price indices. We also retrieve the data split by startup type. This classification of startups will be discussed in Section 3.3.

In Appendix Figures A1–A3, we compare our startup population to Eurostat's Business Demography Statistics on startups (while excluding sole proprietorships for consistency). Figure A1 shows that startup rates (the number of startups in a year as a fraction of the total firm population) are very comparable between our CompNet-based data set and the aggregate data published by Eurostat. The same holds, by and large, when we compare average employment growth during the first five years after startup (Figure A2). In most countries, trend growth in both data sets is very similar. In a few cases—such as the Netherlands and Sweden—there are gaps in the average *level* of reported employees. In those cases, a comparison with other countries suggests the Eurostat data are anomalous, rather than the CompNet data. Finally, Figure A3 compares exit rates (firm death) over time in both data sets. The five-year cumulative exit rate is comparable at 45 percent (56 percent) in the CompNet (Eurostat) data set. Moreover, the trends as firms age are very

[16] We drop firms that are not observed in each year between starting operations and exiting the data set.

[17] These industries are administration; construction; hospitality; ICT; manufacturing; professionals; trade; and transport. Due to confidentiality reasons, cells with fewer than ten underlying firm observations return empty. We also produced results at the more granular two-digit NACE industry level, but this approach created too many empty cells.

[18] We use two productivity measures. The first is labor productivity, defined as real value added per employee. The second is TFP, which is based on a homogeneous production function estimated at the two-digit sectoral level via the two-step control function of Ackerberg, Caves and Frazer (2015). We aggregate TFP using employment shares.

similar in both cases, although in Sweden CompNet tends to overreport firm exit. Overall, we conclude that the firm population that underpins the statistical moments we derive from CompNet is representative of the firm population in our sample countries.

3.3 Identifying startup types

We use K-means cluster analysis (Everitt, Landau, Leese and Stahl, 2011) as a data-driven approach to categorize firms according to their startup strategy. K-means clustering is a type of unsupervised machine learning that has recently gained traction in the applied economics literature as a way to study empirical settings with latent heterogeneity, see for example Bonhomme, Lamadon and Manresa (2022). In our application, the heterogeneity is in firm startup types, and the idea underlying our use of the clustering algorithm is that choices made in the very first year help to reveal the type of startup.

Let x_i be a vector of firm-level clustering variables, in practice converted into z-scores to avoid arbitrary scaling effects. The clustering algorithm allocates each individual firm i into one of $j = 1, .., k$ clusters, in order to solve $\min \sum_{j=1}^{k} \|x_i - \bar{x}_j\|^2$, where $\bar{x}_j$ is the cluster mean. The algorithm begins with k seed values as the initial group means. Each observation is then assigned to the group with the closest mean. Based on that initial categorization, new group means are determined and these iterative steps continue until no observations switch groups.

We experiment with different k's by calculating the statistic $\eta^2 \equiv 1 - \frac{WSS}{TSS}$, where $WSS \equiv \sum_{j=1}^{k} \|x_i - \bar{x}_j\|^2$ is the within-cluster sum of squares and $TSS \equiv \sum_{j=1}^{k} \|x_i - \bar{x}\|^2$ is the total sum of squares, with $\bar{x}$ being the unconditional mean across all observations.[19] We let k vary between 1 and 10, which is visualised in the scree plots in Appendix Figure A4. At $k = 5$, the η^2 statistic is around 0.6, which means five clusters capture around three-fifths of the total variation in the clustering variables. Beyond $k = 5$, the η^2 statistic still increases but levels off. The data therefore suggest that our startups are optimally clustered into five

[19] This statistic has a similar interpretation to the R^2 reported in regression analysis.

well-separated (non-overlapping) clusters, each representing a distinct startup strategy.

We let the algorithm cluster startups based on five important endogenous variables that entrepreneurs decide on when starting a business: the number of employees; real total assets; capital intensity (amount of real fixed assets per employee); cash to total assets; and leverage (total debt to total assets).[20] We therefore cluster using variables that are decided at the moment of startup (but can be adjusted during the life of the firm) rather than outcome variables such as labor productivity or TFP. We choose these variables because the existing literature identifies them as key startup decision parameters and because the underlying CompNet microdata are complete and of high quality across all our sample countries.[21]

3.4 Comparing clustering results across countries

We implement the cluster analysis using a separate micro data set for each country. There is therefore no a priori reason for the clustering outcomes to be similar across countries. Indeed, very different clusters may arise in different contexts. Moreover, even if the clusters would be similar, their shares might vary widely across countries.

To assess the similarity of clusters across countries, we run a second-stage "meta-clustering" analysis, which groups comparable clusters from different countries. This also provides an objective procedure to assign common names to similar clusters. Specifically, we repeat the clustering analysis while taking the cluster centers derived from each country's first-stage clustering as the observations.[22]

The four panels in Figure 1 visually summarize the outcome of this meta-clustering

[20] All monetary variables in CompNet are denominated in thousands of euros.

[21] Earlier work has assessed the role of startups' scale as measured by total assets or employees (Albuquerque and Hopenhayn, 2004; Kerr and Nanda, 2010; Buera, Kaboski and Shin, 2011) or set-up costs (Derrien, Mésonnier and Vuillemey, 2020)); liquidity and cash holdings (Bolton, Wang and Yang, 2019); and leverage and use of bank credit (Robb and Robinson, 2014; Farinha, Félix and Santos, 2019; Derrien et al., 2020; Bustamante and D'Acunto, 2021). We also use individual firms' capital intensity (fixed assets per employee) as a clustering variable because heterogeneity in production functions (and the resulting variation in the elasticity of substitution between capital and labor) is expressed directly in different choices regarding capital-to-labor ratios (Oberfield and Raval, 2021).

[22] That is, in the meta-clustering procedure, the units of observation are the z-scores of the first-stage cluster centers, averaged across years and industries. The z-scores are computed within each country to allow for measurement differences and institutional variation across countries.

procedure. Different meta-clusters are indicated with different colours. The panels clearly show five clusters arising in all countries. For example, the first panel contains a red meta cluster of capital-intensive startup clusters. Each of the individual red circles indicates a country-level cluster of startups that stand out nationally because of their particularly high capital intensity. Such a distinct capital-intensive cluster emerges in each country, thus allowing the algorithm to bunch them together in a single meta-cluster.

Importantly, the variation between clusters within countries is much greater than the variation between countries in the same meta-cluster. In other words, the clusters in different countries are very similar. For the meta-clustering we obtain $\eta^2 = 0.96$. This indicates that variation between clusters explains the vast majority of the overall data variation. Only a very small contribution is left for cross-country variation within meta-clusters.[23]

One might be concerned there are mechanical reasons for the very similar clusters in different countries, or that this similarity is a coincidence. To investigate this, we conduct a Monte Carlo experiment for the meta-clustering. We consider 1,000 random draws for the cluster variables, with means and standard deviations as observed in the data. However, in the experiment, these draws are i.i.d. so that no meta-clusters exist.[24] Each time we compute η^2. Appendix Figure A5 shows that these η^2 statistics are much lower in the experiment than the 0.96 observed in the real-world data. The Monte Carlo experiment therefore supports our interpretation that the cluster outcomes observed in the data are indeed remarkably similar across countries.

4 An anatomy of startup types

This section presents three novel stylized facts that follow directly from our clustering analysis. A first key result is the presence of five distinct startup types across countries, industries,

[23]Another indication of the similarity of clusters across countries is that, in each country, all clusters fall into different meta-clusters. This is not mechanically the case. It could have been the case that the meta-clustering would assign multiple clusters in a country to the same meta-cluster.

[24]We assume log-normal distributions for these draws, as the cluster variables are non-negative.

and cohorts. A second finding is that the initial differences between these five startup types are remarkably persistent over time (Section 4.1). A third important finding is that each of these startup types has a recognizable life cycle in terms of firm traits and performance measures (Section 4.2). Section 4.3 sketches a short profile of each startup type.

4.1 Five types of startup

Table 1 summarizes the results of our clustering analysis. We label the five archetypal startup clusters that emerge *Basic* (49 percent of all startups); *Large* (4 percent); *Capital-intensive* (7 percent); *Cash-intensive* (26 percent); and *High-leverage* (14 percent). These labels reflect the key dimension along which a startup type clearly differentiates itself. For example, large startups employ, on average, 20 people when they begin operations, compared with an average of only three people for the other types. Likewise, cash-intensive startups hold, on average, 54 percent of their assets as cash when they commence operations, whereas the average is just 12 percent for other startups.

Figure 2 shows that, while the clustering algorithm yields the same five startup types in each country, their local prevalence differs somewhat. For example, cash-intensive startups are relatively ubiquitous in Italy but less so in France. Likewise, highly leveraged startups are relatively common in France but less widespread in Croatia, Denmark, and Lithuania.

Figure 3 views the composition of the startup population through a sectoral lens and shows that the five startup types also emerge within each main economic sector. The distribution over the five types nevertheless differs somewhat between sectors. For example, large startups are slightly overrepresented among manufacturing firms but underrepresented among information and communications technology (ICT) firms and enterprises that provide professional services. Cash-intensive firms are overrepresented in the ICT industry and professional services, while high-leverage startups are relatively common in the hospitality sector. This distribution of startup types by industry also varies across countries (see Figure A6 in the Appendix).

Finally, Figure 4 shows that the distribution of startups across the five types (and aggregated over all countries) is quite stable during the period 2000–2019. We observe a small decline in the share of highly leveraged and basic startups, while the share of cash-rich startups steadily increases during the protracted period of monetary easing in the wake of the global financial crisis.

Each of the five startup types also consistently displays its defining characteristic across countries. For example, as can be gleaned from the first panel of Figure A7 in the Appendix, large startups are indeed consistently larger (in terms of total assets) than the four other startup types. In relative terms, this difference is particularly striking in Italy but less so in a country such as Croatia. Likewise, the last panel of Figure A7 shows that high-leverage startups are indeed the most leveraged group of startups in each country, and this is particularly so in Denmark, Lithuania, and the Netherlands.

4.2 Startup types: Early life cycles

4.2.1 Persistence and convergence of the initial choice variables

With the clustering results in hand, we now describe key patterns in the development of startups during the first 12 years of their existence. We first focus on the choice variables that we fed into the clustering algorithm. For each of these, we run age-specific regression specifications in which we regress the clustering variable on dummy variables for four startup types (we omit the *Basic* type as the base group) as well as country, cohort, and industry fixed effects. We use the full panel data set at the one-digit industry level. We run a separate regression for each age group (one-year-old firms, two-year-old firms, etc.) and plot the successive coefficients for the startup type dummies in Figure 5.

A number of salient patterns stand out. First, while *Cash-intensive* startups, by definition, begin their operations with substantially more cash (relative to total assets) than *Basic* and other startup types, they quickly reduce this cash intensity over time as they invest in other assets. Yet, even after 12 years, the cash intensity of this startup type remains about 10 percentage points higher than that of other startups. Second, *Large* startups not only start out with significantly more employees, this size gap vis-à-vis other startup types widens further during the first decade. While large startups employ, on average, 20 more people than basic startups when they commence operations, this difference increases to about 30 employees after 12 years. Third, we find clear evidence of convergence in leverage ratios across startup types. In particular, *High-leverage* startups are about 50 percentage points more leveraged than basic startups when they begin operations (even within the same country and industry). That excess leverage is reduced quickly during the first decade of operations so that, after 12 years, the difference has shrunk to just 5 percentage points. Fourth, we also find (partial) convergence in terms of capital intensity. *Capital-intense* startups begin production with an almost 50 percentage point higher capital-to-employee ratio. Over time, however, they quickly reduce this gap to about 15 percentage points. Fifth and finally, we see that large startups are not only bigger in terms of staff numbers but also in terms of total assets. Yet, while large startups gradually expand their staff numbers even further, relative to other startup types, they slightly reduce the size of their balance sheet, again relative to other startup types in the same country and industry. There is some convergence in the average capital intensity of these large firms over time.

4.2.2 The performance of startup types over time

Next, we are interested in how different types of startups perform as they grow older. To look into this in a systematic way, Table 2 reports panel regressions for several performance measures. Observations refer to cell averages for all new firms in a country, one-digit industry, startup year (cohort), age, and type. For example, an observation could refer to the average productivity of Spanish ICT firms in the *High-leverage* category established in 2005, at age seven. We include dummies to indicate the four main startup types, again using the *Basic* type as the excluded category. We saturate the specifications with an exhaustive set of interactive fixed effects (FE) to flexibly control for unobservable drivers of firm-level performance that might correlate with startup type. In particular, country-cohort FE absorb all time-invariant characteristics common to startups established in a specific country and year; industry-cohort FE control for time-invariant traits common to all startups in a specific industry and established in a given year; and country-industry FE absorb all time-invariant variation that characterizes startups in a specific industry and country. Finally, we add interactions between startups' age and their country, industry, and cohort. This allows us to flexibly control for startup traits that are specific to the country, sector, or year of establishment *and* that depend on a firm's age.[25]

Panel A of Table 2 reveals several interesting patterns. First, compared to firms with a basic startup strategy, startups with a more differentiated strategy outperform in terms of higher labor productivity (column 1) and TFP (column 2), as well as a lower likelihood of early exit (column 3). In particular, *Large* startups are considerably less likely to exit within the first decade after commencing operations. This cluster operates at a below-average profit margin (column 5)—even relative to other startups in the same country, sector, and industry—partly because they pay substantially higher wages (column 4).

Also of interest are the highly leveraged firms. This cluster of startups consistently and strongly underperforms in terms of labor productivity and TFP. Highly leveraged firms also tend to operate with a lower profit margin (column 5) even though they pay lower wages compared to the other startup types (column 4).

In Panel B of Table 2, we replicate this analysis using only firms between five and eight years old. The results line up closely with those in Panel A, indicating that the performance divergence between startup types is not solely driven by transient differences in early life.

[25]Throughout the paper, we provide robust but unclustered standard errors as we use data for the full population of startups across sectors and countries rather than for a random sample of these (Abadie, Athey, Imbens and Wooldridge, 2017). All results are robust to clustering at the sector-country-cohort level to account for possible correlation of model errors over time at that level.

4.3 Startup types: Profiles

This section provides a short profile for each startup type in order to consolidate and interpret the results from our empirical exploration so far in light of the existing literature.

4.3.1 Capital-intensive startups

About 7 percent of all startups belong to the capital-intensive cluster. A plausible narrative for the existence of capital-intensive types concerns heterogeneity in production functions, with some firms having a particularly high production function elasticity with respect to capital. Oberfield and Raval (2021) provide evidence for heterogeneity in production elasticities and derive implications for the macroeconomy, such as the aggregate labor share of income. Our results underscore the importance of such heterogeneity, and provide further insights into the life cycles and performance of firms with particularly high capital intensities.

From the start, capital-intensive firms use more fixed assets per employee, possibly reflecting the lumpiness of initial investments (Doms and Dunne, 1998; Cooper and Haltiwanger, 2006). Over time, their capital intensity—gradually and partially—converges with that of other startup types. This suggests that, as demand grows, capital-intensive startups can scale up production by increasing the number of employees that utilize the substantial stock of machines and other assets. For example, firms may start with a core of highly skilled employees and hire additional lower-skilled staff as they grow. In some sample countries, our data indeed show a fall in wages per employee as capital-intensive startups mature.

Notwithstanding a partial adjustment process during the first decade, there is in fact a strong persistence in these startups' reliance on capital in the production process (Figure 5). This not only reflects the industries in which capital-intensive startups tend to operate (such as manufacturing and transport) but also their chosen production strategy (such as a high degree of automation). Even after more than a decade, capital-intensive startups continue to stand out—also relative to other firms in the same industry or country—by the sheer amount of fixed assets they employ. They remain about three times as capital-intensive as firms in the other startup clusters.

Empirical evidence has shown that capital-intensive firms are prone to complement valuable fixed assets with high-quality human capital (Doms, Dunne and Troske, 1997). In line with this, we observe that capital-intensive startups pay higher wages than most other firm types and, unsurprisingly, boast higher labor productivity. They also operate at high levels of TFP, suggesting that they combine physical and human capital in a more productive way. As a result, their medium-term survival prospects are relatively good.

4.3.2 Large startups

About 4 percent of all startups belong to the *Large* cluster. Large firms are relatively common in construction, transport and logistics, and manufacturing. These firms commence operations with both a large number of employees (more than five times as many as other startups) and a substantial asset base, reflecting their use of a scalable production technology and access to a scalable demand base. This is consistent with empirical findings in Sterk r al. (2021), who use US data to document the importance of ex ante heterogeneity for firm-level employment.

Size heterogeneity may derive from TFP differences combined with decreasing returns to scale (which implies that more productive firms choose a larger optimal size) or from heterogeneity in returns to scale, with some production processes being scaled up relatively easily. A final possibility is that size heterogeneity reflects differences in the scalability of the demand for firms' products. Hottman, Redding and Weinstein (2016) show that differences in the scale of demand is a quantitatively important source of heterogeneity across firms.

Our results again shed light on the life-cycle structure and performance of heterogeneous firms, this time along the size dimension. Large startups are relatively productive and, importantly, this productivity premium is very persistent over time. They scale up their workforce even further during the first 12 years of their existence (thus diverging even more from other firm types in terms of employee numbers).

Large startups display high TFP when compared to both basic and high-leverage startups, at levels similar to capital-intensive and cash-intensive startups. This good productivity performance also allows large startups to pay relatively high wages. This is in line with an extensive literature documenting a firm-size wage premium (Brown and Medoff, 1989; Oi and Idson, 1999; Troske, 1999). We show that this premium already exists when comparing very young firms in the same country and industry. Moreover, large startups operate on modest profit margins, passing much of their productivity gains on to consumers.

Even though they are quite leveraged, the overall advantages of size—such as more diversification—make large startups the least likely to exit during the first 12 years of operations. This is in keeping with an established literature documenting a positive relationship between firm size in early life and subsequent survival (Dunne, Roberts and Samuelson, 1988; Geroski, Mata and Portugal, 2010; Branstetter, Lima, Taylor and Venâncio, 2014).

4.3.3 High-leverage startups

About 14 percent of all startups belong to the *High-leverage* cluster. These firms begin operations by taking on substantial amounts of debt relative to the size of their balance sheet (their average leverage ratio is 116 percent). While high-leverage startups are present in all sectors, they are relatively common in accommodation and food services, and, to a lesser extent, administrative and support services.

Interestingly, during their early life, these firms immediately deleverage, suggesting they may be financially quite vulnerable. High-leverage startups have the lowest 12-year survival probability. This aligns with an earlier literature documenting a possibly causal link between firm leverage and exit probability.[26] Dinlersoz, Kalemli-Özcan, Hyatt and Penciakova (2019) show that young private firms in the US tend to be highly leveraged but deleverage as they age. We find a similar pattern within the high-leverage cluster of star-

[26] See, for example, Chevalier (1995) and Kovenock and Phillips (1997). Zingales (1998) shows for the US trucking industry that initial leverage (at the beginning of a deregulation period) increased the probability of subsequent default. An important channel is highly leveraged firms' impaired ability to invest, as also shown by Lang, Ofek and Stulz (1996).

tups. At the same time, we also show that, while firms in this cluster deleverage over time, their leverage remains persistently above that of other young firms. This persistence has been demonstrated previously by Lemmon, Roberts and Zender (2008) on the basis of Compustat data for publicly listed firms (and not conditioning on firm types). The authors document that, while leverage ratios exhibit substantial convergence, they are also remarkably stable over long periods of time. We also find both a transitory and a permanent component in leverage ratios in our cross-country startup data.

High-leverage startups exhibit relatively low levels of productivity, and it often takes several years for them to become profitable at all.[27] This cluster consequently pays considerably lower wages than all other startup types, even within the same industry or country. There are several reasons why highly leveraged firms tend to underperform in terms of productivity, profitability, and survival probability. One option is that these firms are costly to establish (for example, because an intensive marketing campaign is needed) and these fixed set-up costs are funded with bank debt (Derrien et al., 2020).

An alternative explanation for why startups with low initial leverage subsequently perform better is based on the insight that, at the time of startup, the information asymmetry between banks and firms is highest. Firms with high-quality investment projects, who know they soon will become very profitable, may not want to delay investment but instead settle for accessing (relatively little) credit early on (Bustamante and D'Acunto, 2021). A third possibility is that firms with high initial leverage are run by subsistence entrepreneurs with a high "utility value" of being an entrepreneur but with limited business skills (Schoar, 2010). While such firms are typically only moderately profitable, subsistence entrepreneurs may nevertheless raise debt if banks accept personal collateral (so that the business owner is personally liable in case their enterprise goes bankrupt).

[27] Rajan and Zingales (1995) provide cross-country evidence of a negative correlation between profitability and leverage. This is in line with pecking-order theory, which posits that profitable firms prefer to use their internal funds (retained earnings) over external debt (Myers and Majluf, 1984).

4.3.4 Cash-intensive startups

About one-quarter of all startups belong to the *Cash-intensive* cluster: these are typically smaller startups with a high ratio of cash to total assets. At startup, these firms hold almost half of their assets in the form of cash, about five times as much as firms in the other startup clusters. They are more common in the administrative, ICT, and professional services sectors, and typically do not grow much over time. Because these firms keep a large buffer of liquid assets, the proportion of fixed assets such as machinery is initially relatively low (importantly, this holds even *within* sectors). Cash-intensive startups are therefore also firms with a quite low capital intensity.

Over time, cash-intensive firms reduce their liquidity as they gradually convert some cash holdings into tangible and intangible fixed assets. Although their cash ratio consequently comes down, a persistent gap remains vis-à-vis the other startup clusters. Even after 12 years, the cash intensity of this startup type remains about 10 percentage points higher than that of other young firms. Interestingly, the performance of cash-intensive startups is excellent, also compared to other enterprises in the same sector. They have high levels of labor productivity, TFP, and profitability, and consequently also pay somewhat higher wages. These patterns are in line with Begenau and Palazzo (2021), who show that public firms with a high expected productivity growth, and hence a bigger need for future investment, operate with a higher initial cash-to-assets ratio.

Many cash-intensive startups are small services firms run by highly skilled individuals. The services they provide typically require few machines or other fixed assets and are only to a limited extent scalable. Few additional employees are hired over time. The results suggest that, rather than producing homogeneous goods at scale for a mass market, many cash-intensive startups instead sell to a profitable niche market of heterogeneous consumers, for example by implementing a differentiated strategy based on targeted advertising (Johnson and Myatt, 2006). These startups do not need to borrow much to commence operations, and therefore consistently display the lowest leverage ratio of all clusters. This also suggests that they use (internal) cash buffers rather than (future) access to credit as a precaution against demand shocks. This strategy may be optimal because these firms own few tangible assets that could serve as collateral, or because they are relatively non-standard, making it difficult to obtain bank credit.

4.3.5 Basic startups

Finally, just fewer than half of all startups make up the *Basic* cluster. This largest startup cluster looks average across all the dimensions discussed so far (Table 1). When they begin operations, these firms employ, on average, four people; operate with a capital intensity of 8.6 percent; have a cash ratio of 12 percent; and a leverage ratio of 23 percent. Basic startups conduct operations at a level of labor productivity and TFP that is lower than that of all other startup types, except for the highly leveraged ones. Productivity growth is muted too. After a decade, basic startups still operate at relatively low TFP, labor productivity, and profitability levels.

The presence of a large group of basic startups that follow an undifferentiated strategy and perform relatively poorly, is in line with recent work highlighting the productivity gap between, on the one hand, a small group of well-performing firms that operate at the technological frontier and, on the other hand, a long tail of less-productive laggard firms (Hsieh and Klenow, 2009; Andrews, Criscuolo and Gal, 2016). Our clustering analysis indicates that such a uneven productivity distribution already emerges when new firm cohorts are born.

5 Policy experiments

We now perform counterfactual policy exercises to study how changes in taxation can improve specific macroeconomic outcomes by changing the composition of new startup cohorts. We do this using the model framework developed in Section 2. As explained in that section, to quantify how tax policy affects startup composition, we need the life-cycle profile of each startup type. In addition, we need a second set of statistics: the entry elasticities for each type. We first discuss how we estimate these elasticities and then present our policy exercises.

5.1 Estimating entry elasticities

To estimate entry elasticities, we run a regression based on the entry condition, Equation (1). A challenge, however, is that we do not observe the ex ante expected firm value $\ln \mathbb{E}_j V$ but rather the ex post average realization $\ln V_j$. The difference between the two is because of common shocks that occur *after* entry. If we were to estimate Equation (1) based on ex post realizations, the residual would contain $\ln V_j - \ln \mathbb{E}_j V$, giving rise to correlation between the residual and the right-hand side variable, $\ln V_j$. This would introduce a bias. A second issue is that, under a null hypothesis of free entry (a baseline assumption in the theoretical literature), the entry elasticity is infinite, making the regression specification ill-defined. To circumvent these problems, we rearrange Equation (1) as:

$$d \ln V_j = \frac{1}{\varepsilon_j} d \ln n_j + \xi_j + u_j$$

where $\xi_j \equiv \frac{\gamma_j}{\varepsilon_j}$ is a fixed effect due to entry shocks, for which we control in the regression. Moreover, $u_j \equiv d \ln V_j - d \ln \mathbb{E} V_j$, which is orthogonal to n_j since ex post shocks are not known at the time of entry, and thus cannot affect the number of entrants, n_j.

We use observations at the country(c)-industry(i)-type(j)-cohort(t) level, with corresponding indices between brackets. We control for shocks to the number and distribution of entrants at the country-industry-type level, as well as at the country-industry-year level by using interactive fixed effects at these levels. The former is important as the number of potential entrants may naturally vary by country, industry, and type. The latter captures that, in a specific industry in a given country, the number of potential entrants may fluctuate over time.[28] This gives rise to the following regression specification, which we estimate via

[28] Implicit in our specification is the assumption that, within a country-industry cell, shocks over time to the number of *potential* startups are common across types.

ordinary least squares (OLS):

$$\ln V_{c,i,j,t} = \beta_0 + \beta_1 \ln n_{c,i,j,t} + \xi_{c,i,j} + \xi_{c,i,t} + u_{c,i,j,t}.$$

We note that $\frac{1}{\beta_1}$ is the entry elasticity and that, under free entry (that is, an infinite elasticity), it holds that $\beta_1 = 0$.

A final question is how to measure $\ln V_j$ in the data. We do so using each startup type's life-cycle profile for profits and exit rates, and the number of entrants for each country-industry-type-cohort in our data set.[29] We assume a discount factor $\Lambda = 0.96$, corresponding to an annual discount rate of about 4 percent. We only use cohorts that we observe for at least seven years (that is, those established before 2011) and drop observations beyond age seven. For age eight and onward, we assume that profits and the year-on-year exit rate remain fixed.[30]

Figure 6 plots the estimates for the inverse entry elasticity, β_1. The vertical dashed line denotes an estimate from a regression that does not condition on startup type. This overall estimate is 0.495, implying an entry elasticity of around two. This estimate is significantly different from zero at the 1 percent level, thus rejecting the traditional free-entry assumption. Our overall estimate is in the ballpark of those from estimated structural DSGE models.[31]

The figure also shows the estimates of the inverse elasticity by firm type, illustrating substantial heterogeneity. Basic startups show the highest entry elasticity, about 5.3, whereas large startups have an entry elasticity of around 1. As we discuss in Section 5.2.2, this cross-type heterogeneity in entry elasticities is an important reason why even an undifferentiated, uniform policy change has a different impact on different startup types.

[29] We reconstruct profits by multiplying profits (Earnings Before Interest and Tax (EBIT)) per unit of revenue with revenues, at the country-industry-startup type-cohort level.

[30] That is, we compute the firm value at age zero as: $\ln V_0 = \sum_{a=0}^{6} \Lambda^a s_{0,a}\pi_a + s_{0,7}\pi_7 \sum_{a=7}^{\infty} \Lambda^a s_{6,7}^a = \sum_{a=0}^{6} \Lambda^a s_{0,a}\pi_a + \Lambda^7 s_{0,7} \frac{\pi_7}{1-\Lambda s_{6,7}}$ where $s_{k,l}$ is the survival rate between age k and $l \geq k$. In practice, the component of the value beyond age seven is relatively unimportant for the overall startup value, due to both discounting and the high exit rates in young age groups.

[31] Gutiérrez et al. (2022) and Sedláček and Sterk (2017) find an estimate of around 1.5 and 5.5, respectively.

It is not unexpected that basic startups react relatively flexibly to changes in economic conditions, as the creation of these startups is, for the most part, uncomplicated. Other types may require more specific expertise, which fewer potential entrepreneurs possess. For example, founding a large startup—this cluster begins with, on average, 20 employees and scales up further during the first years of operation—likely requires a more complex business plan than starting a smaller and simpler firm does.

5.2 Counterfactual experiments

5.2.1 A budget-neutral tax policy differentiated by startup type

We can now proceed with our policy experiments. Specifically, we consider the aggregate effects of changes in tax/subsidy policies via the startup composition channel. As explained in Section 2, to quantify the composition channel, we do not need to take a stance on the precise nature of the tax reform. All that matters for this channel is the direct effect of the reform on the tax payments of firms, as a fraction of the firm value, for the different startup types. Thus, the following results apply to a wide range of policy changes in the taxation and/or subsidization of startup firms.

To fix ideas, however, we present the results as a change in corporate income taxation, differentiated by startup type. This is without loss of generality, but makes the magnitude of the tax reform easy to interpret since, in this case, the tax payments as a fraction of the firm's value simply equal the tax rate itself. Furthermore, we do not quantify the effects on post-entry behavior of firms, since this *does* depend on the specifics of the tax reform, and has been widely studied in a large literature, unlike the composition effects.

To impose discipline, we further restrict ourselves to policies that are revenue-neutral.[32] This implies that, if some startup types are to be taxed less, other types need to be taxed more. We also limit ourselves to policies of no more than a 20 percentage points change

[32]To be precise, they are revenue-neutral excluding potential tax revenue effects due to changes in post-entry behavior.

in the corporate tax rate for each type. Aside from these restrictions, we search the entire space of policy changes differentiated by type, and evaluate the macroeconomic implications for any admissible policy.

Our policy experiments are based on a numerical Monte Carlo procedure. Specifically, we consider a large number of uniform random draws for the tax policies and rescale them to ensure they are (post-reform) budget neutral. Then, based on the estimated entry elasticities, we evaluate the change in the number of firms within each type. This allows us to construct counterfactuals for the share $\omega_{a,j}$. Based on this, we then calculate counterfactual macroeconomic aggregates, exploiting that the post-entry behavior of firms is not affected by the corporate income tax. This enables us to compute macroeconomic aggregates using the life-cycle profiles estimated from the data. We compute the macro outcomes for firms up to age 12, the oldest for which we have estimated the life-cycle profile, while accounting for the exit rate of each type (which we also estimate from the data). Figure A8 summarizes the life-cycle profiles we use in the analysis.[33]

Once we have evaluated the macro outcomes for the entire space of admissible policies, we group policies into bins according to their intensity, as measured by the maximum absolute change in the tax rate across types. The idea is that larger policy changes may bring about greater macro-economic effects, but may also face stronger political resistance. It is therefore useful to study the policy space conditional on a certain intensity of the policy. For each bin, we compute policies that bring about the largest positive and the largest negative change in a macro variable (aggregate productivity or employment). We label this the policy frontier and present the tax-rate changes that generate the policy upper bound.

Are large aggregate gains possible? Figure 7 summarizes the aggregate results of our policy experiment. Panel A presents the policy space for aggregate labor productivity. The horizontal axis measures the intensity of the potential policy change (that is, the maximum

[33]We also consider a version that includes firms older than 12 in the computations, which we achieve by extrapolating the life-cycle profiles. The results are very similar to our baseline findings.

change in the tax rate across all firms). Moving from left to right, warmer colors indicate stronger corporate tax-rate differentiation. The solid (dashed) line plots the policy upper bound (lower bound). This is the largest possible aggregate employment increase (decrease) given a certain policy intensity.

The figure shows that substantial macroeconomic gains are possible. For the maximum policy intensity of 0.2 (that is, policies in which the tax rate does not change by more than 20 percentage points for any firm) aggregate labor productivity can be increased by 4.5 percent by shifting the composition of startup types. At the same time, substantial macroeconomic losses are also possible for policies that shift the composition away from high-productivity startup types.

Panel B of Figure 7 again plots the policy space, this time for aggregate employment. Substantial employment gains are possible: 11 percent for a policy intensity of 0.2. At the same time, even higher employment losses are possible for policy changes that move the distribution of startups away from high-employment types.

Which startup types to encourage? The two panels on the left of Figure 8 plot the corporate tax-rate policies associated with the two policy upper bounds. Likewise, the two panels on the right show the associated firm shares. Which startup types should policy encourage in order to increase productivity or aggregate employment?

The upper left panel shows that, in order to achieve the productivity upper bound, taxes should be lowered for capital-intensive, cash-intensive, and large types, financed by an increase in tax rates for basic and high-leverage types. The upper right panel shows that, as a result, the share of capital-intensive startups increases, as do the shares of high cash ratio and large startups. Accordingly, the shares of high-leverage and basic startups falls. Since labor productivity is relatively low among the latter types, the shift in startup composition increases aggregate labor productivity.

The lower left panel of Figure 8 presents the tax rates associated with the employment frontier. In order to boost aggregate employment, tax rates should be lowered for the large type, as well as for the capital-intensive and high-leverage types, which leads to an increased share of these types (lower right panel).[34] This tax cut is then financed by an increase in tax rates for the cash-intensive types, and as a result their population share falls.

The aforementioned increase in aggregate employment of 11 percent is to a large extent driven by a higher number of startups, which increases by up to 7.5 percent. This is because the frontier policy reduces (increases) tax rates for startup types with relatively high (low) entry elasticities, thus resulting in more firm entry.

Policy trade-offs. Of course, most policymakers look beyond aggregate employment and productivity. As discussed in Section 2, the overall welfare effects of a policy change may crucially depend on the externalities that different startup types have on workers and consumers (and the taxpayer, if the reform is not budget neutral).

To analyze policy trade-offs, Figure 9 provides scatter plots that depict pairs of changes in aggregate or average macroeconomic outcomes resulting from each potential policy (again, up to a policy intensity of 0.2). The top left panel shows that, generally, there is some trade-off between increasing aggregate employment and labor productivity: the two outcomes are negatively correlated across possible policy changes. This negative correlation partly reflects that cash-intensive startups are more productive but smaller than high-leverage startups. Subsidizing cash-intensive startups at the expense of high-leverage ones therefore increases labour productivity but reduces employment, at the aggregate level.

Yet, there exist specific policy reforms that simultaneously boost (or reduce) aggregate labor productivity and employment, e.g. by increasing the shares of large and cash-intensive startups as much as possible (given a certain policy intensity). Interestingly, there is a fairly strong negative trade-off between aggregate employment and TFP (top middle panel). On the other hand, policies associated with higher aggregate labor productivity also tend to

[34] The increase in the share of large startups is relatively modest, due to their low entry elasticity. On the other hand, large startups have many more employees on average, and therefore even a small increase in their share can have sizeable aggregate effects.

increase TFP (top right panel).

Policymakers may also be interested in effects on workers. The middle row of Figure 9 shows trade-offs between average wages and aggregate outcomes. Policies boosting aggregate employment through a different startup mix tend to lower average wages, whereas policies that increase aggregate productivity are associated with higher wages. As one might expect, some productivity gains are passed on to workers, increasing welfare beyond firm owners.

The bottom row of Figure 9 plots profit margins to provide insight into the effects on consumers. We observe that policies that increase employment tend to reduce profit margins, which may be to the benefit of consumers. By contrast, policies to boost productivity increase profit margins, suggesting that the productivity gains are, at least in part, reaped by firm owners as opposed to consumers.

5.2.2 A uniform policy reform that is not budget-neutral

So far we have focused on budget-neutral reforms, differentiated by startup type. We now consider a uniform cut in the corporate tax rate of 1 percentage point for all startup types. Of course, this reform is no longer budget neutral. An alternative interpretation of this policy is a reduction in entry cost by 1 percent (expressed in terms of the entry cost of marginal entrants).

Based on our model, it turns out that aggregate employment increases by 3 percent due to this uniform policy. This is substantial, but less than some of the differentiated, budget-neutral reforms we considered before. These could boost aggregate employment by more than 10 percent. The 3 percent employment increase is entirely driven by an increase in the number of firms. In contrast, average firm size decreases by 0.24 percent, which mainly reflects the low entry elasticity of large startups. These startups thus respond less to the tax cut and, as a result, their share in the overall firm population falls. Similarly, we also find a decline in aggregate labor productivity and TFP.

An important insight from our model is therefore that the aggregate effects of a uniform policy intervention can be dampened by selection effects between types. This finding is in line with recent empirical literature. For instance, Branstetter et al. (2014) find that a uniform reduction in the entry costs for new entrepreneurs in Portugal led to more job creation, but that marginal entrants were smaller and less productive. Our previous analysis indicates that an appropriately targeted policy can bring substantial positive selection effects, thereby creating a greater and/or more cost-effective boost to macroeconomic performance.

5.2.3 Selection effects within types?

The macroeconomic effects of the policies analyzed above are due to selection effects between different types of startups. As explained previously, in the model there is no entry selection within types. To test whether such entry selection can indeed be ruled out empirically, we run age-partitioned regressions for all startups and where observations are at the country-sector-type-cohort level (for example, Spanish construction firms of the cash-rich startup type that were established in 2017).

For each age, we regress an outcome variable—such as labor productivity or employment—on the (log) number of firms in a cohort to estimate the relationship between cohort size and later startup performance. We fully saturate the regressions with interactive fixed effects at the country-sector-type, country-sector-cohort, country-type-cohort, and sector-type-cohort levels. If there is positive selection within types, cohorts with more startups should exhibit inferior performance later in life (when absorbing all variation that may correlate with cohort size through the use of the aforementioned battery of interactive fixed effects).

Figure A9 shows the results for firms up to age 10. The estimated effects are mostly insignificant, economically small, and do not trend in any particular direction. This indicates that—in line with our model—there is little within-type selection at the entry stage.

5.2.4 Equilibrium effects

We now revisit our baseline policy experiment, while accounting for equilibrium effects, as discussed in Section 2.5. Such effects may be especially relevant if an EU-wide policy were to be implemented. Concretely, we endogenize the real wage, compute the composition of startups using Equation (3), and impose the labor market clearing condition (4) as well as budget-neutrality. That is, we solve numerically for the (change in) the equilibrium wage that clears the labor market given the policy change.

To implement this exercise, we set $\kappa = 0.5$, which is in the ballpark of estimates for the Frisch elasticity in the literature. The elasticity of the firm value with respect to profits is given by $\gamma_j = -\frac{\mathbb{E}_j \sum_{t=0}^{\infty} \beta^t \Lambda^t w L_{t,j}}{V_{t,0}}$. That is, $-\gamma_j$ is the ratio of the present-value wage bill to the present value of profits. We can compute this based on our data, given we observe the firms' wage bills. We use the same truncation procedure for the present-value wage bill as for the firm value.

Figure A10 presents the results. When we account for equilibrium effects, the policy space for aggregate productivity turns out to be very similar to our baseline results. The space for employment effects is somewhat smaller. This is to be expected as an increase in labor demand pushes wages up, dampening the increase in aggregate labor demand.

5.3 Tax differentiation for startups in practice

Our counterfactual exercise illustrates how applying differentiated corporate tax rates across startup types can bring about substantial macroeconomic gains in terms of higher aggregate employment and/or labor productivity. While such differentiation should in principle be possible, as it distinguishes startup types on the basis of a few observable characteristics, the practical implementation or political feasibility could be challenging.[35]

Yet, in practice it may not be necessary to differentiate policies explicitly by startup type,

[35] One challenge may be that startups alter their initial choices to mimic types that are more favorably taxed, although in practice this can be costly as the observed choice differences across startups are large.

as it is possible to exploit the heterogeneous exposure of different firm types to unconditional policies. To give an example, a more favourable tax expensing regime for capital investments would disproportionately benefit capital-intensive and (to a lesser extent) large startups, as the capital intensity of these types is relatively high (see Table 1). Such an unconditional policy would therefore create a change in the startup composition towards these types, pushing up aggregate productivity and employment. Our framework can be readily applied to quantitatively evaluate the composition effects of any such unconditional policy proposal.

Notwithstanding the potential pitfalls of differentiated policies, various countries have already implemented startup policies that, either implicitly or explicitly, distinguish between startup types (as well as between startups and more mature firms). First and foremost, several countries explicitly differentiate corporate tax rates based on firm size, as measured by the number of employees and/or total taxable income. Belgium, France, Hungary, Latvia, Lithuania, Luxembourg, the Netherlands, Poland, Portugal, Slovakia, and Spain all apply reduced corporate tax rates to firms below a certain size threshold.[36] Likewise, the US federal government levies a 35 percent top rate for companies with at least USD 10 million in annual profits, while smaller firms benefit from lower rates. A few countries differentiate tax rates among startups specifically. For example, the rate that applies to Indian manufacturing startups depends directly on their annual turnover (Kalra, 2019).

Our results indicate that tax policies that explicitly penalize large firms can have adverse effects on the startup composition, thus reducing macroeconomic performance and possibly welfare. Indeed, we show that large startups not only create a disproportionate amount of new jobs but also pass their relatively high productivity levels on to workers and consumers. Similarly, our results suggest that size-contingent regulations—such as less onerous public-reporting requirements, looser entry regulation (Klapper, Laeven and Rajan, 2006), or less costly labor legislation (Garicano, Lelarge and Van Reenen, 2016; Aghion, Bergeaud and

[36] See Bergner, Brautigam, Evers and Spengel (2017) and OECD (2021b). The largest difference between the reduced and the standard tax rate can be found in Portugal, where large businesses pay a rate of 31.5 percent, while small businesses pay a reduced rate of 17 percent on taxable income below a certain threshold.

Van Reenen, 2019) for small firms—may adversely affect the composition of new startup cohorts, as they effectively discourage the entry of relatively large startups.

Second, several countries engage in implicit forms of tax differentiation among small businesses and startups. These include subsidies and grants, accelerated depreciation measures, investment allowances, as well as tax credits, breaks, and exemptions (OECD, 2020). Such measures can lower the effective tax rate for small and young businesses substantially (Rosenberg and Marron, 2015). In some cases, tax benefits only apply to startups with a particular funding structure. These include special credit guarantees and loans for startups. Other measures, such as the UK Enterprise Investment Scheme (EIS) and Seed Enterprise Investment Scheme (SEIS) help startups to attract equity funding by offering tax relief to investors who buy new shares in startups.

Our results suggest that schemes to help startups access debt or equity funding can have strong impacts, through the startup composition channel, on the performance of new generations of firms. In particular, we find that high-leverage startups tend to perform very poorly compared to other types. Government policies that facilitate startups' access to credit may therefore have very different impacts on startup performance than measures that help new firms to broaden their equity base.

Third, many countries offer specific tax advantages to startups that invest in R&D and innovation. R&D tax credits and allowances are particularly common (OECD, 2021a). Qualification for such tax credits often depends on basic firm characteristics that are similar to those in our cluster analysis. Other countries have introduced regulatory simplifications in order to break down entry barriers for innovative startups. An example is Italy's 2012 startup act (Menon, DeStefano, Manaresi, Soggia and Santoleri, 2018). Our results suggest that the aggregate productivity impact of such R&D tax advantages or regulatory easing depends directly on the take-up by the different types of startups.

The above discussion illustrates how many countries already operate policies, be it corporate taxes or other instruments, that in some way or form differentiate, often implicitly, between types of startups.[37] The resulting variation in effective tax rates is often substantial and reflective of policy goals such as job creation or innovation-driven productivity growth. Many of these real-world examples of corporate tax differentiation can be easily translated to, or nested in, our more general policy exercise.

6 Conclusions

This paper combines a novel and comprehensive data set on startups in multiple European countries with a theoretical framework to help understand the potential macroeconomic gains of tax policies to encourage a better mix of startups. Using unsupervised machine learning, we find that very similar clusters of startups (identified by the choices they make at entry) emerge in each of these countries. Moreover, the subsequent performance of these types—in terms of employment, productivity, and survival—differs strongly. There are therefore potential macroeconomic gains (or losses) to be made from policies that affect startup types differently and that alter the composition of new startup cohorts.

Applying policy exercises based on the theoretical framework and the empirical results, we find that these macro gains or losses can be quantitatively substantial. Moreover, our results inform how policy can be changed to achieve these macroeconomic gains. An important insight from our model is that the aggregate effects of a *uniform* policy intervention can be dampened by selection effects between startup types. Re-designing tax policy to proactively tilt the startup composition towards high-performance types (large and capital intensive startups) and away from low-performance types (basic and high-leverage startups) may then be a cost-effective and forward-looking way to improve macroeconomic outcomes in the decades to come. Such a change in the startup mix may be attractive not only from an aggregate perspective, but also from a welfare point of view, since high-performance startup types tend to pass on gains to workers, in the form of more and better-paying jobs, and

[37] Because both the type of investments and the financial structure of startups differ across industries, there also exists substantial cross-sector variation in effective tax rates (Rosenberg and Marron, 2015).

consumers, in the form of modest profit margins.

Our empirical strategy and theoretical framework are easy to implement and extend to non-tax policies such as entry regulations. This makes it a straightforward complement to standard analyses evaluating the macroeconomic effects of particular policy reforms, which typically ignore impacts on the composition of new startup cohorts.

Increasingly, statistical agencies make rich administrative micro data sets on firms available for research purposes. Our methodology can therefore readily be applied to a wider set of countries. It would also be interesting to explore if an even more granular classification of startup types could be exploited to design more fine-tuned policies. Finally, it would be useful to consider to what extent differences in startup composition can account for cross-country heterogeneity in macroeconomic performance. We leave these issues for future research.

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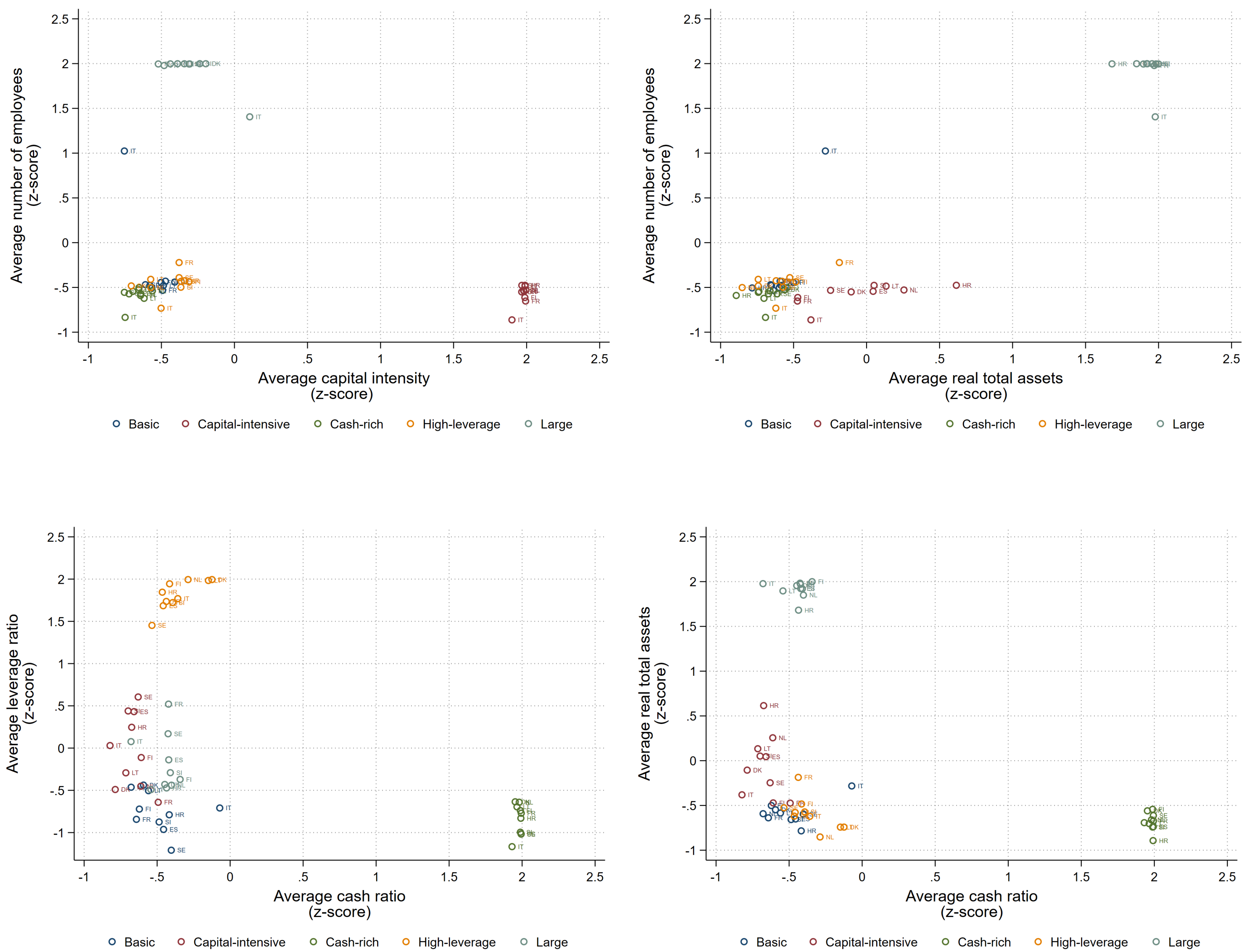
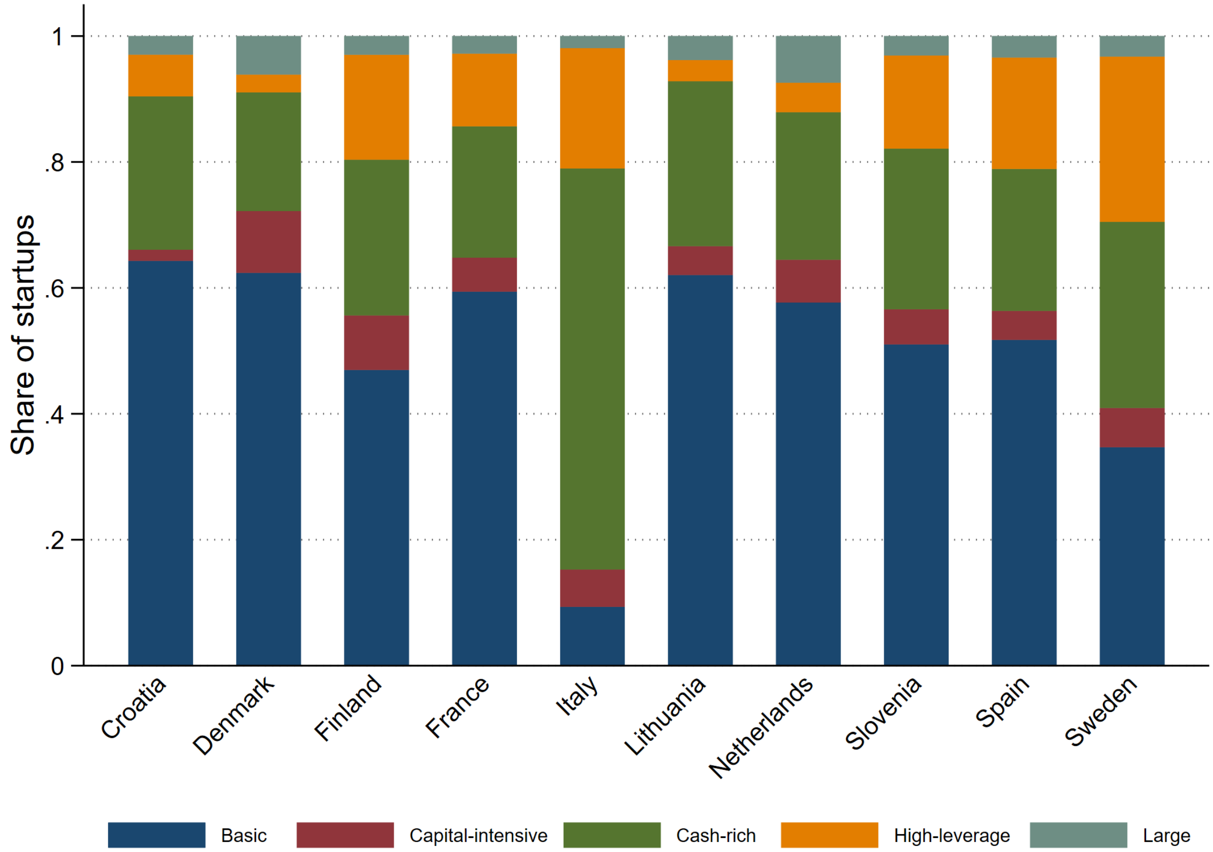
Tables and Figures

Figure 1. Meta-clustering of startup types



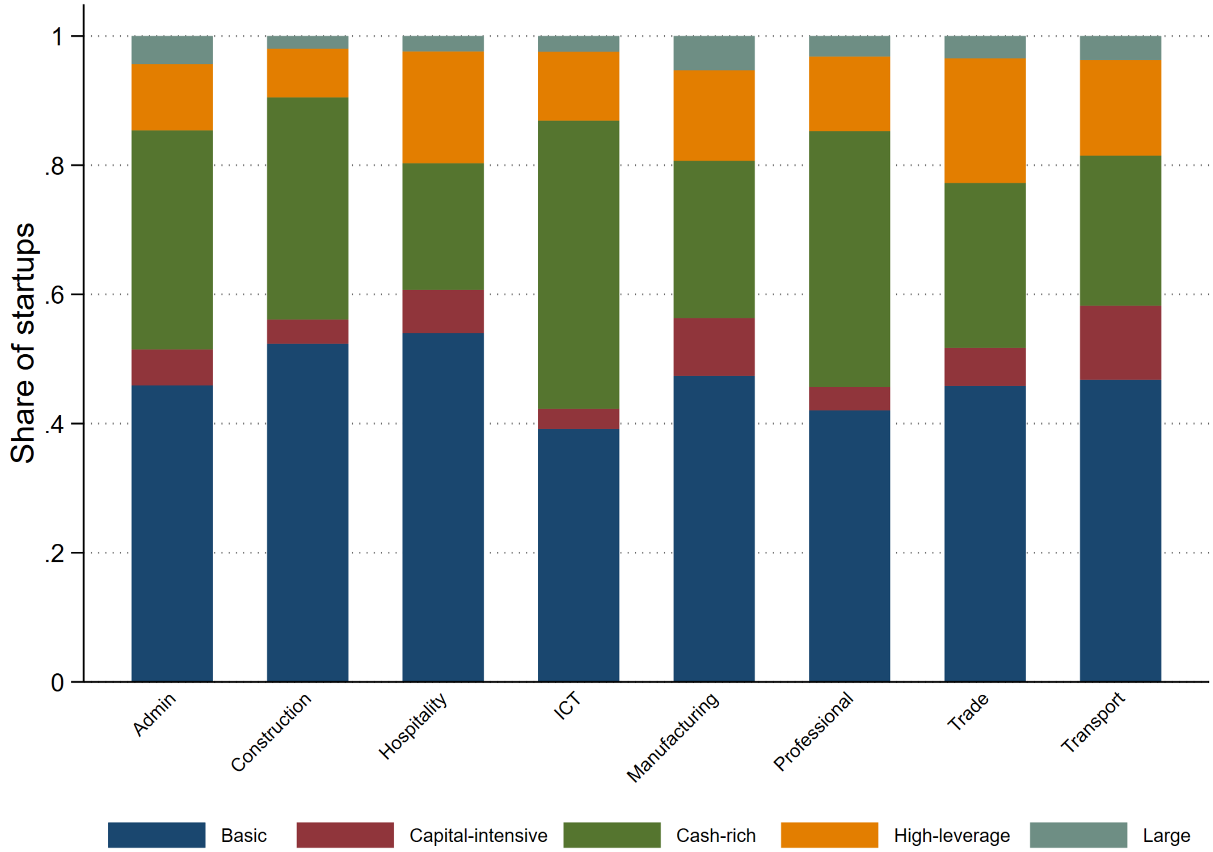
Notes: The four panels in this figure summarize the meta-clustering procedure. Different meta-clusters are denoted by different colours. The meta-clustering groups comparable clusters from different countries by taking the cluster centers derived from each country's first-stage clustering procedure as the observations. More specifically, in the meta-clustering procedure, the units of observation are z-scores of the first-stage cluster centers, averaged across years and industries.

Figure 2. Distribution of startup type by country



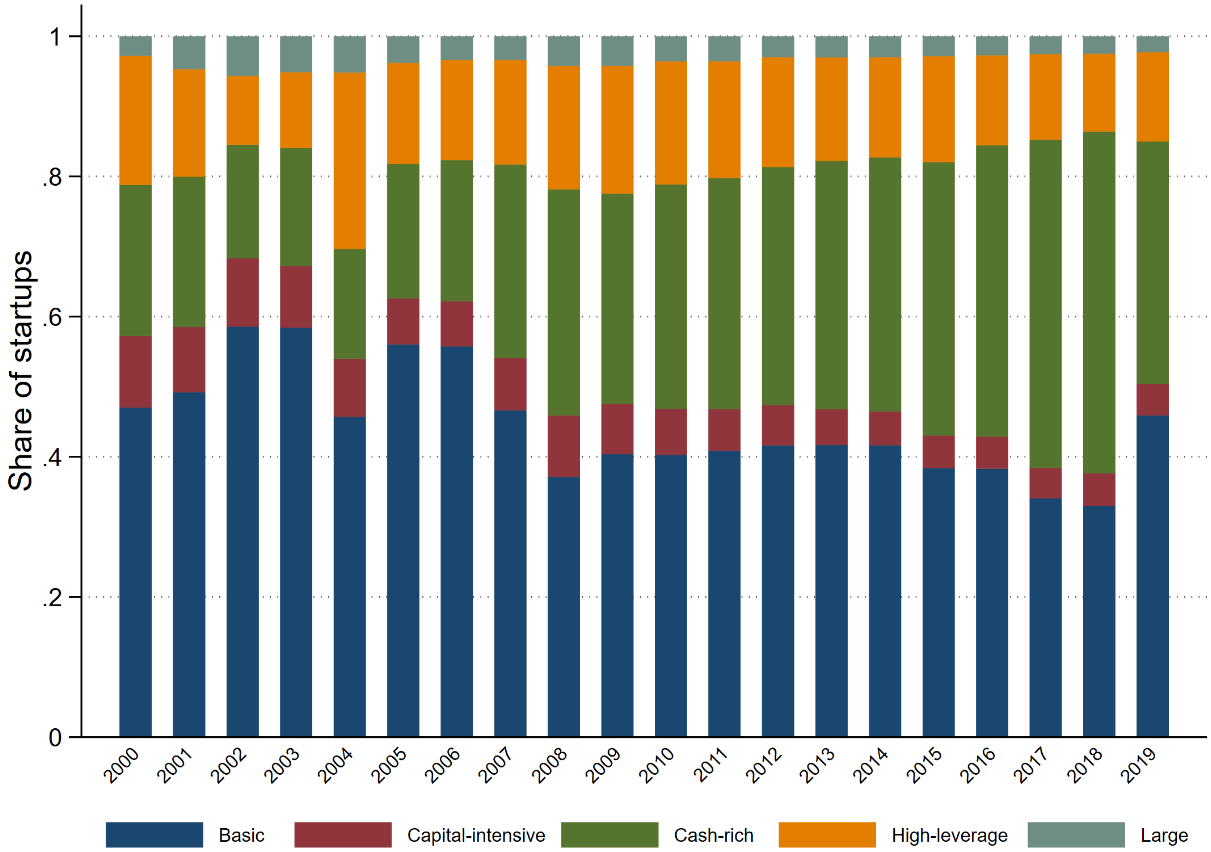
Notes: This figure illustrates the distribution of the startup population for individual countries across the five startup types. The startup population comprises all cohorts available for each country.

Figure 3. Distribution of startup type by industry



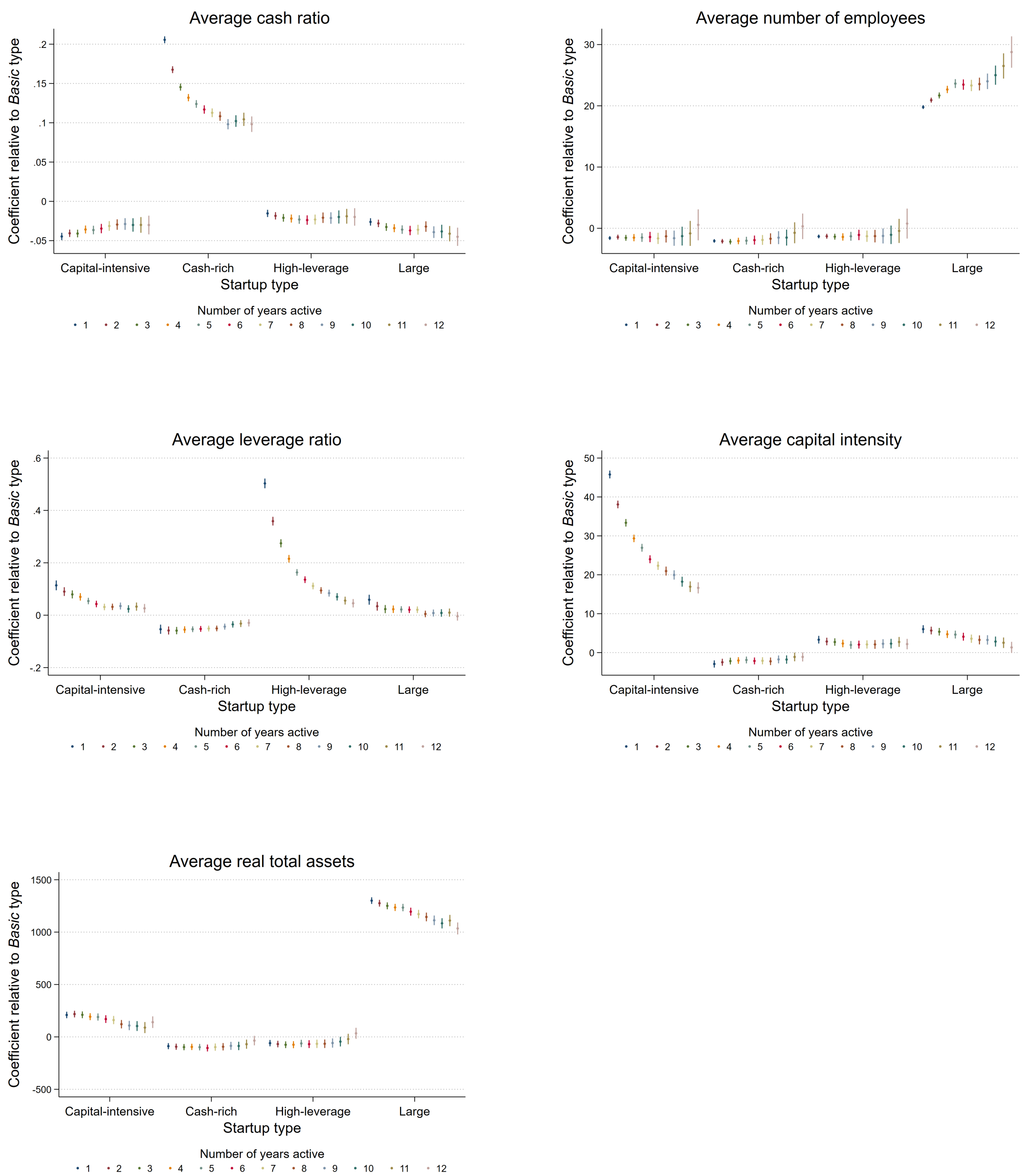
Notes: This figure illustrates the distribution of the startup population for one-digit NACE Rev.2 industries across the five startup types. The startup population comprises all cohorts available for each country.

Figure 4. Distribution of startup type by cohort



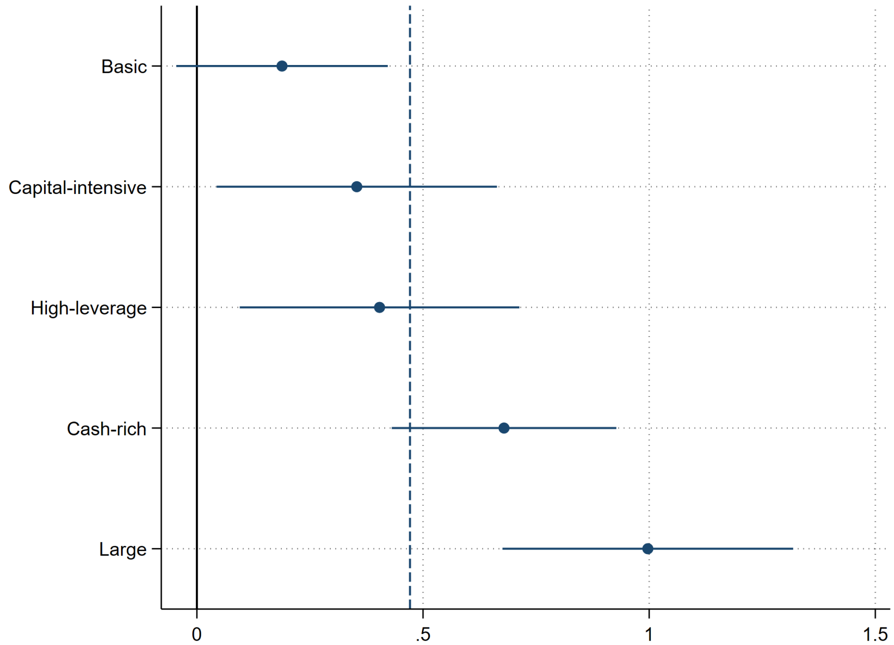
Notes: This figure illustrates the distribution of the startup population for each cohort across the five startup types.

Figure 5. The life cycle of startup types



Notes: The panels in this figure summarize how the startup types develop during the first 12 years of their life in terms of the five clustering variables. Each panel corresponds to one clustering variable and plots the coefficients from 12 separate regressions where the dependent variable is this variable. Each regression is then run for an age group (age is 1, 2, ...12 years). For example, the first panel summarizes regressions in which the *Average cash to total assets* ratio is regressed on dummy variables for the startup types (the *Basic* type is omitted) as well as country, cohort, and industry fixed effects. The sample is the full panel data set at the one-digit industry level.

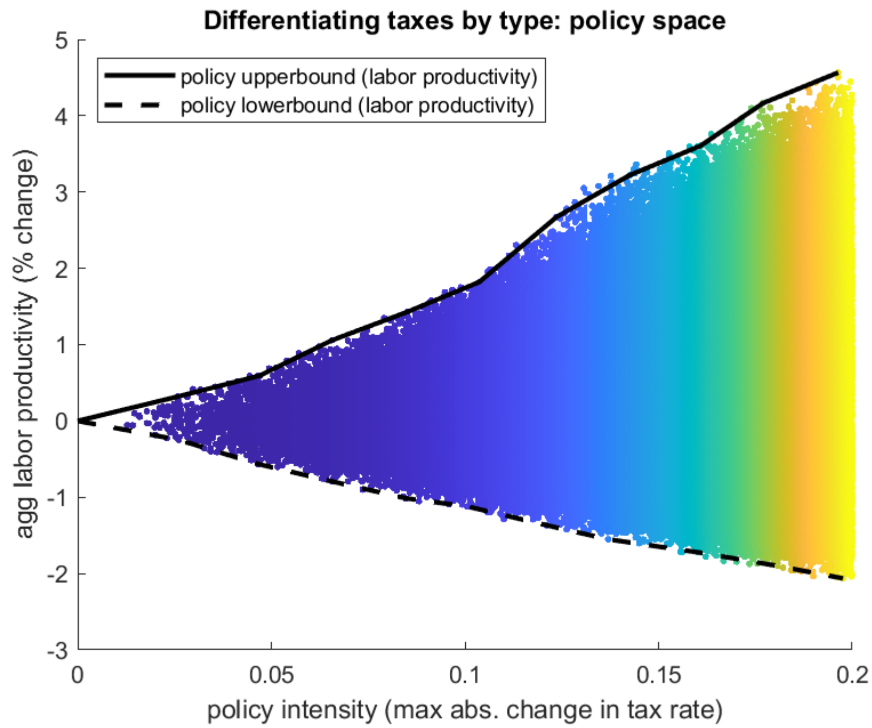
Figure 6. (Inverse) entry elasticities by startup type



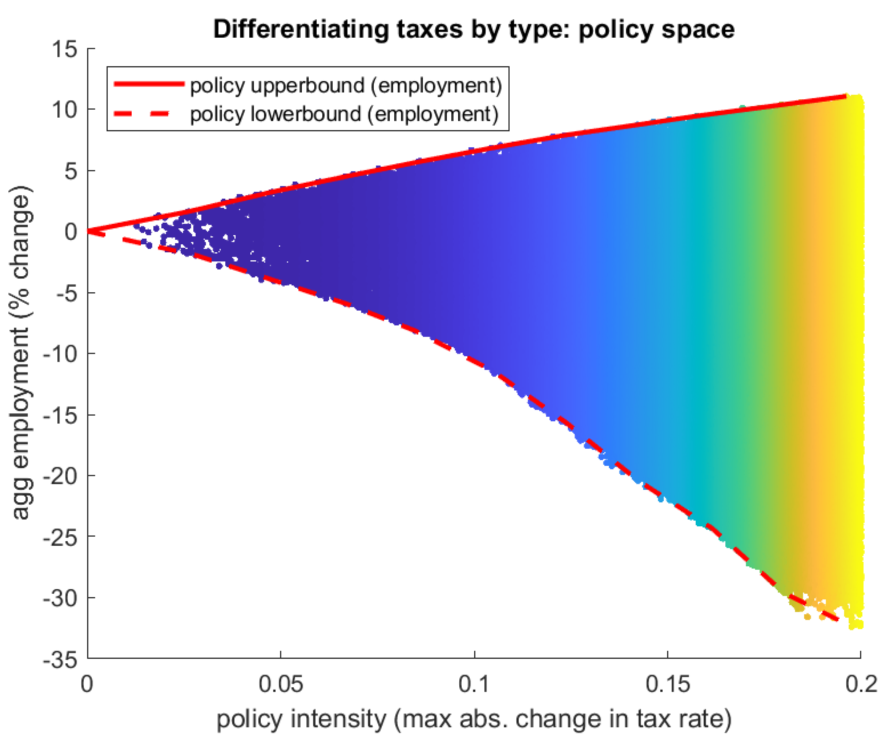
Notes: This figure shows coefficients from OLS regressions where the dependent variable is the log net present value of firm profits. The estimated coefficients represent the inverse entry elasticity, β_1, for each startup type. *Country* $\times$ *Startup type* $\times$ *Industry* and *Country* $\times$ *Industry* $\times$ *Cohort* fixed effects are included throughout. The regressions are at the one-digit NACE Rev.2 industry level. The data set only includes cohorts observed for at least seven years (those founded before 2011) and drops observations beyond age seven. For age eight and onward, profits and the year-on-year exit rate are assumed fixed. Confidence intervals are at the 95 percent level. The vertical dashed line denotes an estimate from a regression that does not condition on startup type.

Figure 7. Policy experiment: Tax differentiation, aggregate labor productivity, and employment of young firms

Panel A

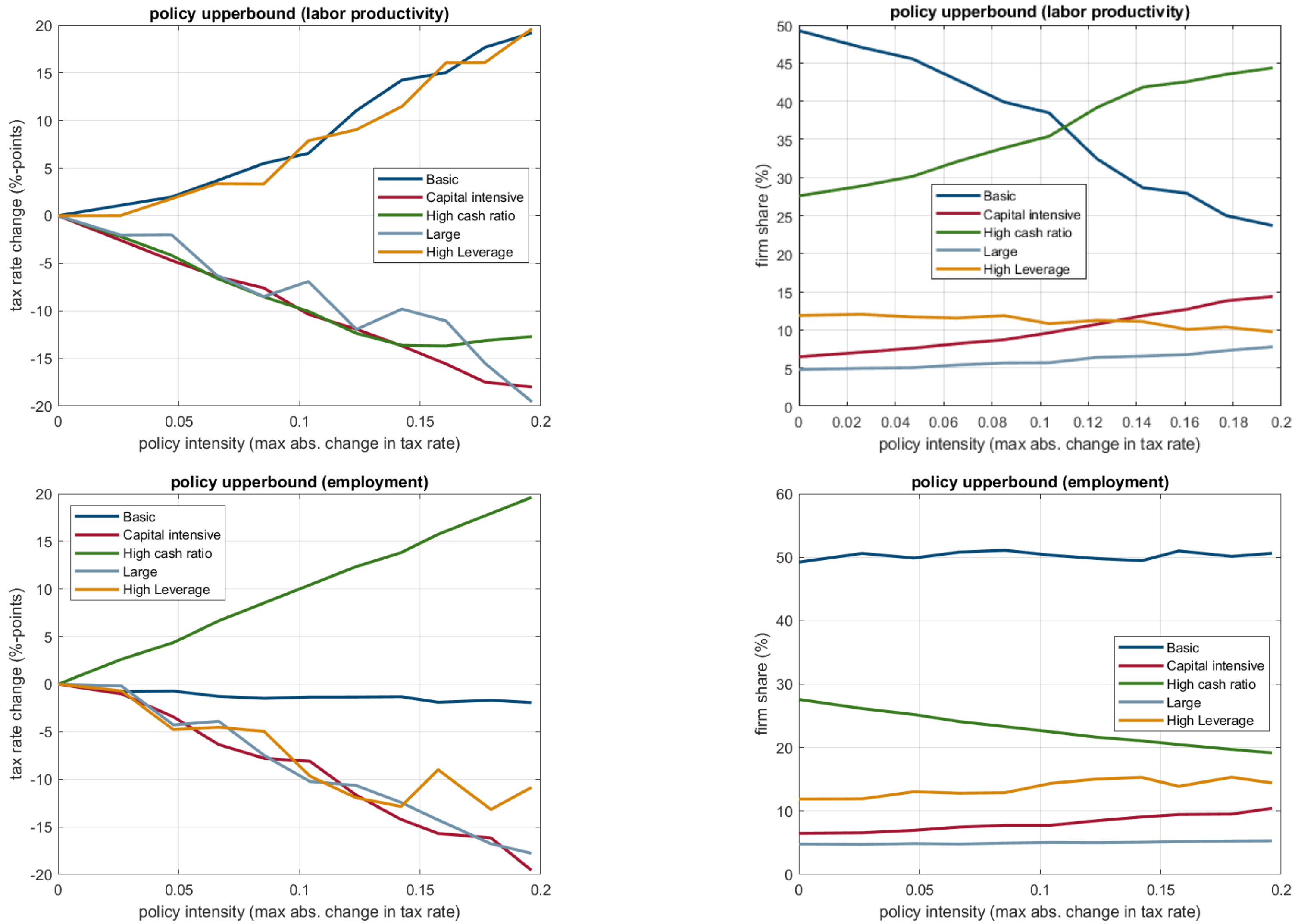


Panel B



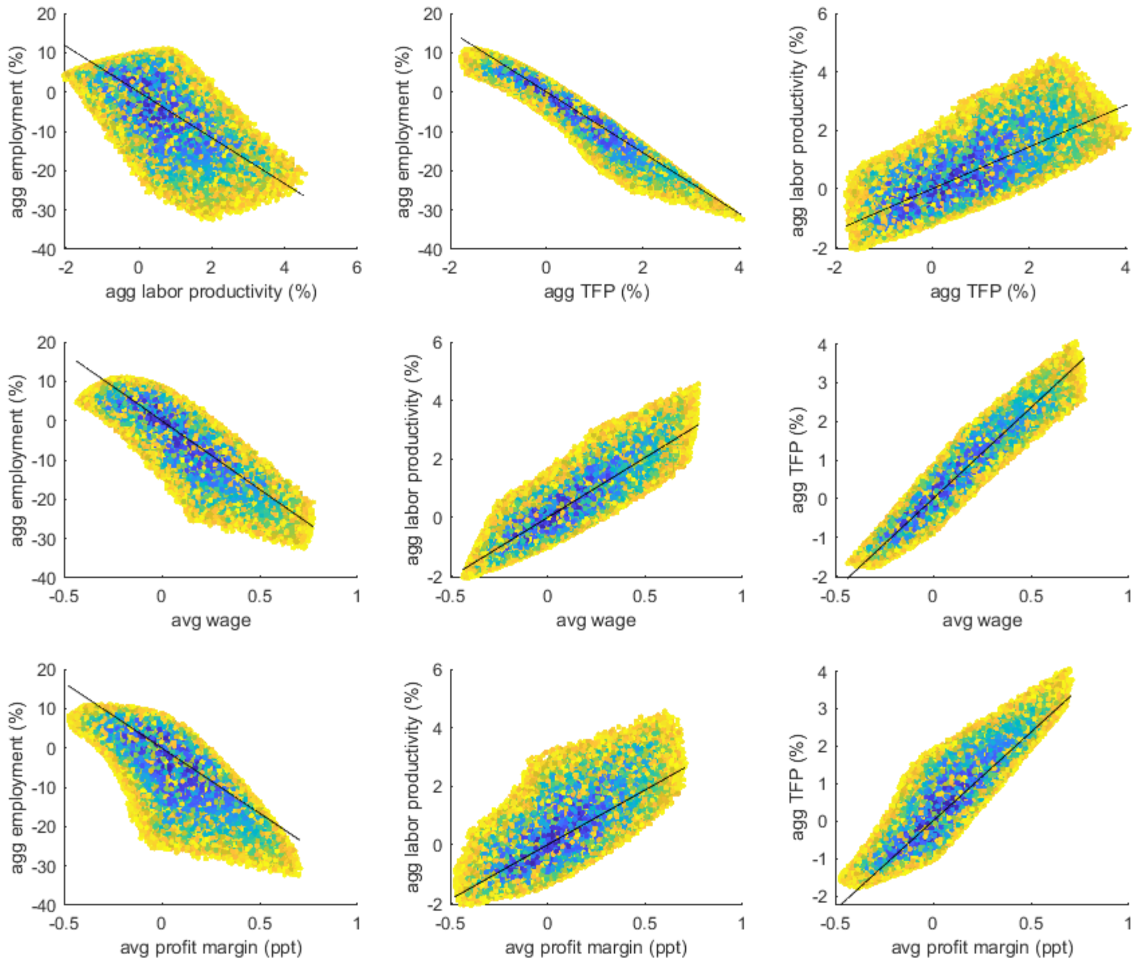
Notes: This figure summarizes the policy experiment. Panel A shows the policy space for aggregate labor productivity. The horizontal axis measures the intensity of the potential policy change as the maximum absolute change in the tax rate. Warmer colors indicate stronger corporate tax rate differentiation. The solid line plots the "policy upper bound": the largest possible aggregate labor productivity increase given a certain policy intensity. Similarly, Panel B plots the policy space for aggregate employment.

Figure 8. Policy experiment: Upper bounds of macro impacts due to tax differentiation



Notes: The two panels on the left (right) plot the corporate tax rate policies (startup shares) associated with the two policy upper bounds. The upper left (right) panel shows the tax rates (startup shares) associated with the labor productivity frontier. The lower left (right) panel shows the tax rates (startup shares) associated with the employment frontier.

Figure 9. Policy experiment: Macroeconomic trade-offs



Notes: These scatter plots each depict pairs of changes in aggregate or average macroeconomic outcomes resulting from each potential policy (up to a policy intensity of 0.2). Wages per employee are in thousands of euros. Linearly fitted regression lines are shown in black.

Table 1. Characteristics of startup types at time of entry

	(1)	(2)	(3)	(4)	(5)
	No. of employees	Capital intensity	Real total assets	Cash ratio	Leverage ratio
Basic	4	8.56	166.59	0.12	0.23
Capital-intensive	2	93.18	405.12	0.09	0.41
Cash-intensive	2	4.67	92.46	0.54	0.18
High-leverage	3	12.90	122.97	0.14	1.18
Large	20	16.05	1488.30	0.13	0.34

Notes: This table presents the cross-country means of the cluster variables for each of the five startup types in the year of establishment. Means are unweighted and based on the full panel.

Table 2. Startup types and firm outcomes

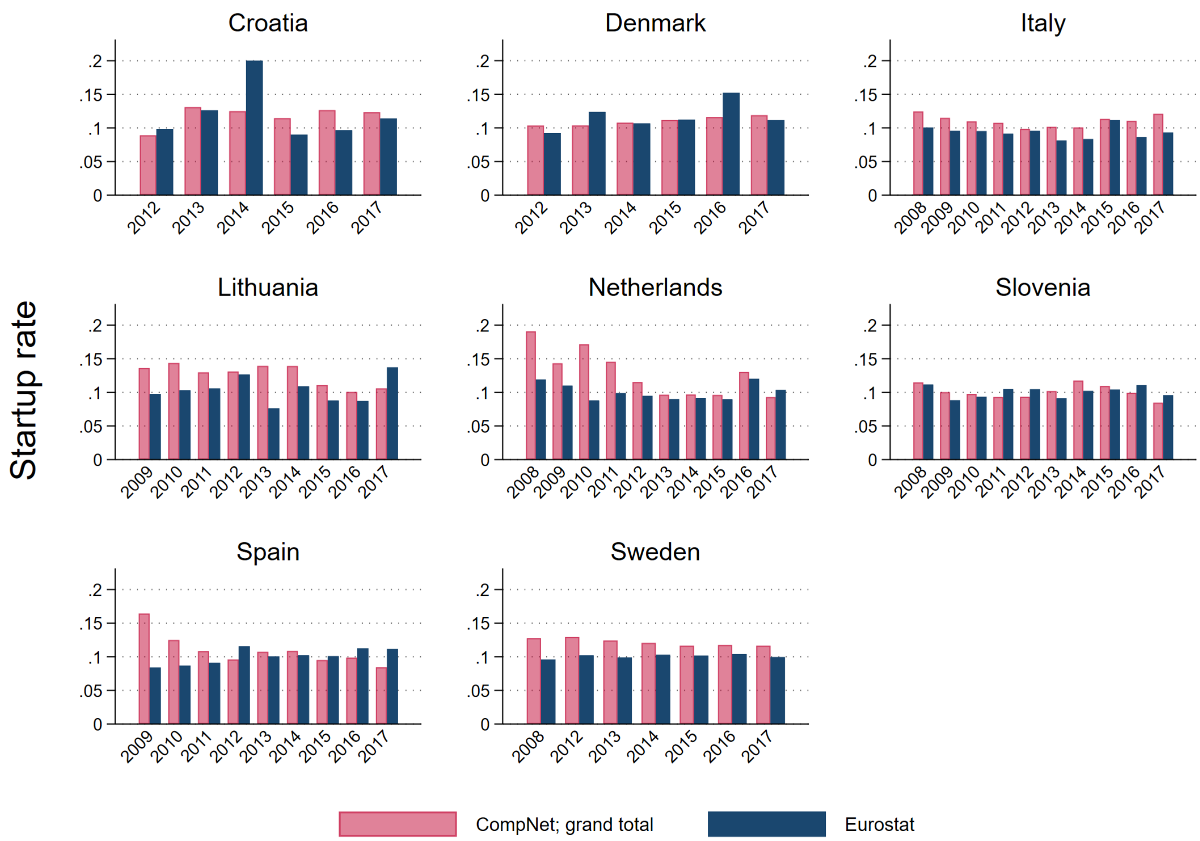
Panel A: All firms					
	(1)	(2)	(3)	(4)	(5)
	Aggregate labor productivity	Aggregate TFP	Average exit probability	Average wage per employee	Average profit margin
Capital-intensive	0.315***	0.048***	-0.061***	2.449***	0.012***
	(0.005)	(0.004)	(0.003)	(0.094)	(0.001)
Cash-rich	0.032***	0.050***	-0.007***	1.092***	0.022***
	(0.003)	(0.002)	(0.002)	(0.058)	(0.001)
High-leverage	-0.045***	-0.039***	-0.000	-1.516***	-0.031***
	(0.004)	(0.003)	(0.002)	(0.064)	(0.001)
Large	0.165***	0.046***	-0.124***	3.406***	-0.018***
	(0.004)	(0.003)	(0.003)	(0.094)	(0.001)
Constant	3.353***	2.213***	0.710***	27.732***	0.041***
	(0.002)	(0.002)	(0.001)	(0.033)	(0.000)
R-squared	0.905	0.978	0.635	0.909	0.605
N	27,562	19,848	29,642	28,744	28,490

Panel B: All firms, aged 5-8					
	(1)	(2)	(3)	(4)	(5)
	Aggregate labor productivity	Aggregate TFP	Average exit probability	Average wage per employee	Average profit margin
Capital-intensive	0.195***	0.011*	-0.063***	0.879***	0.013***
	(0.007)	(0.006)	(0.003)	(0.121)	(0.001)
Cash-rich	0.019***	0.031***	-0.023***	1.145***	0.014***
	(0.006)	(0.004)	(0.003)	(0.095)	(0.001)
High-leverage	-0.027***	-0.021***	0.002	-1.394***	-0.008***
	(0.006)	(0.005)	(0.003)	(0.105)	(0.001)
Large	0.151***	0.050***	-0.141***	2.596***	-0.013***
	(0.007)	(0.007)	(0.004)	(0.154)	(0.001)
Constant	3.464***	2.247***	0.812***	30.151***	0.048***
	(0.003)	(0.003)	(0.001)	(0.052)	(0.001)
R-squared	0.906	0.981	0.616	0.930	0.654
N	8,731	6,055	9,569	9,149	9,081
Country × cohort FE	✓	✓	✓	✓	✓
Industry × cohort FE	✓	✓	✓	✓	✓
Country × Industry FE	✓	✓	✓	✓	✓
Age × Country FE	✓	✓	✓	✓	✓
Age × Industry FE	✓	✓	✓	✓	✓
Age × Cohort FE	✓	✓	✓	✓	✓

Notes: This table shows OLS regressions where the dependent variable is indicated in the column heading. Observations are at the country x sector x startup type x cohort x age level. The dependent variables in the first two columns are aggregate outcomes (i.e. employment-weighted averages) by startup type. The dependent variables in the last three columns are simple averages by startup type. Industries are defined at the one-digit NACE Rev.2 level. Regressions are based on the full panel of firms younger than nine years in Panel A and firms between age five and eight in Panel B. Standard errors are in parentheses. *, **, *** indicate significance at the 10, 5, and 1 percent level, respectively. Wages are denominated in thousands of euros.

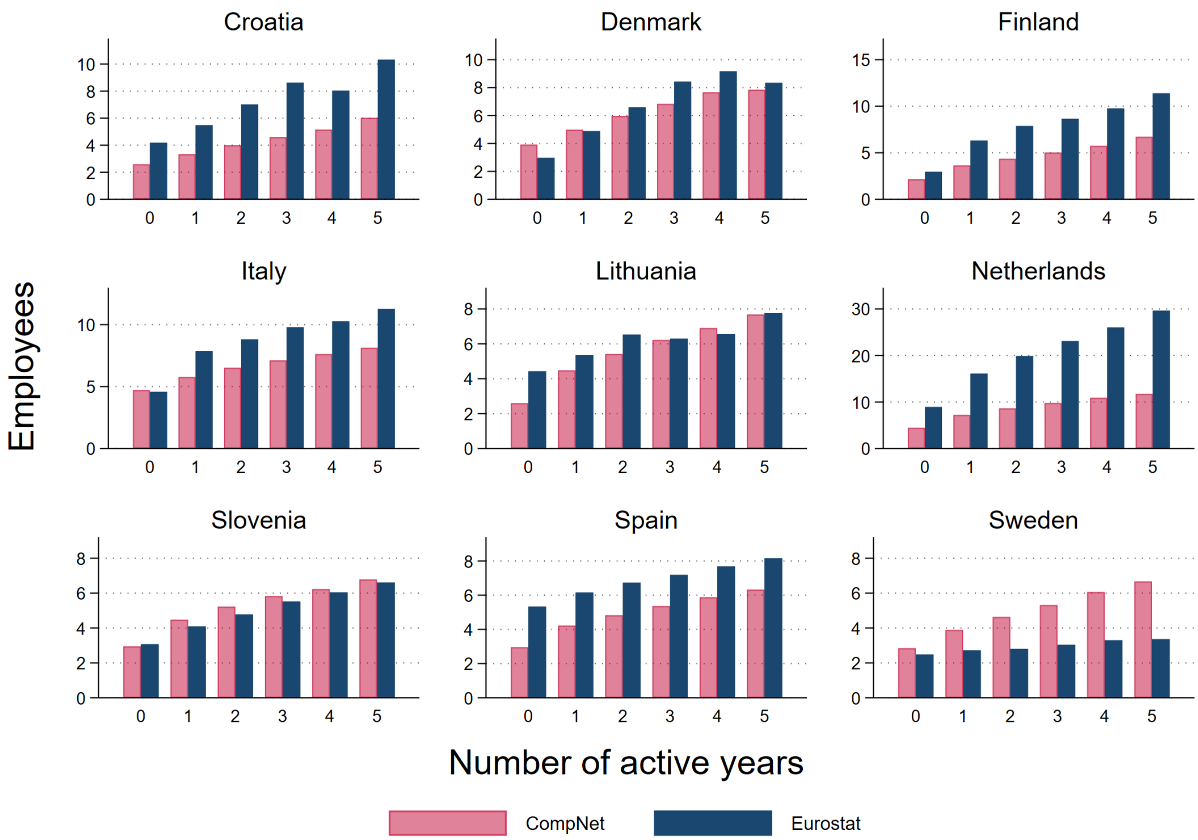
Appendices

Figure A1. Startup rates by cohort and country—CompNet versus Eurostat data



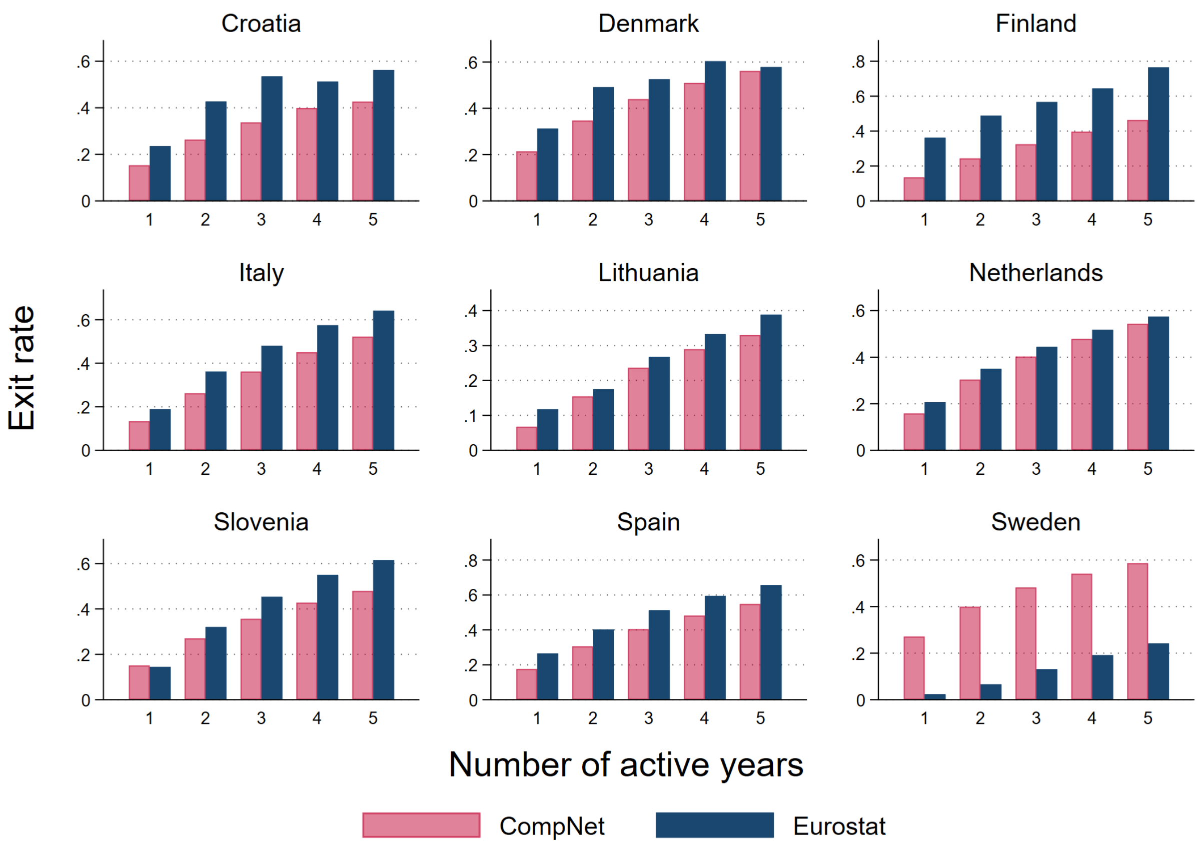
Notes: This figure compares the total number of startups in the CompNet database (pink bars) with establishment of firms in Eurostat (blue bars). Cohorts reported are subject to data availability. Finland is omitted in this chart because we cannot access the total number of startups in the CompNet database for that country. France does not appear as Eurostat does not report firm entry prior to 2008.

Figure A2. Employment by firm age—CompNet versus Eurostat data



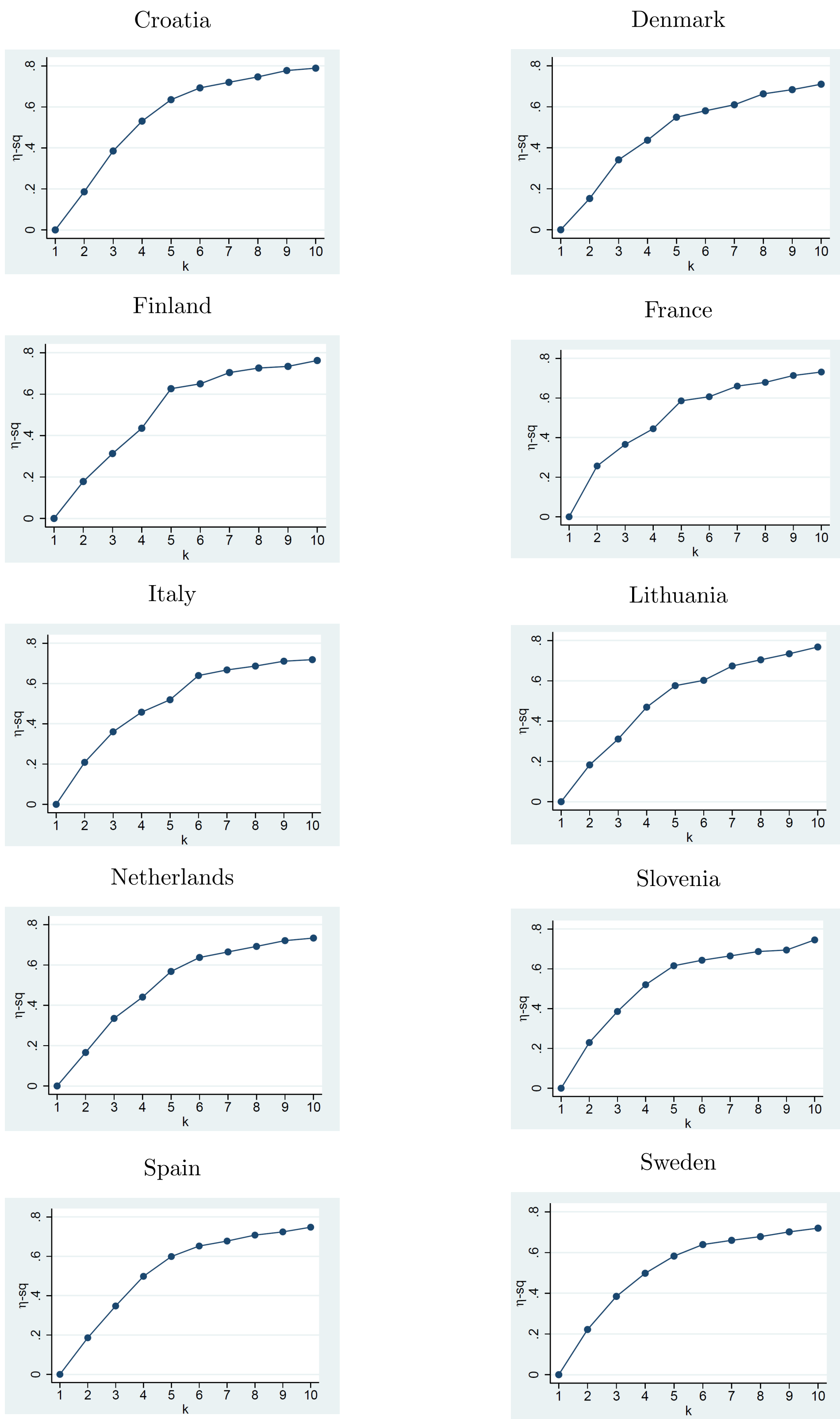
Notes: This figure compares growth in number of persons employed by startups as reported by CompNet (pink bars) and Eurostat (blue bars). CompNet and Eurostat data are matched based on the startup cohort and age group. For comparison purposes, we adjust the Eurostat data such that sole proprietorship firms are removed and we adjust for the average number of persons employed by sole proprietorship firms. The x-axis depicts *Startup age*, which is the number of years a startup has been active. *Employees* on the y-axis is averaged over cohorts. France does not appear as Eurostat does not report firm entry prior to 2008.

Figure A3. Cumulative exit rates by firm age—CompNet versus Eurostat data



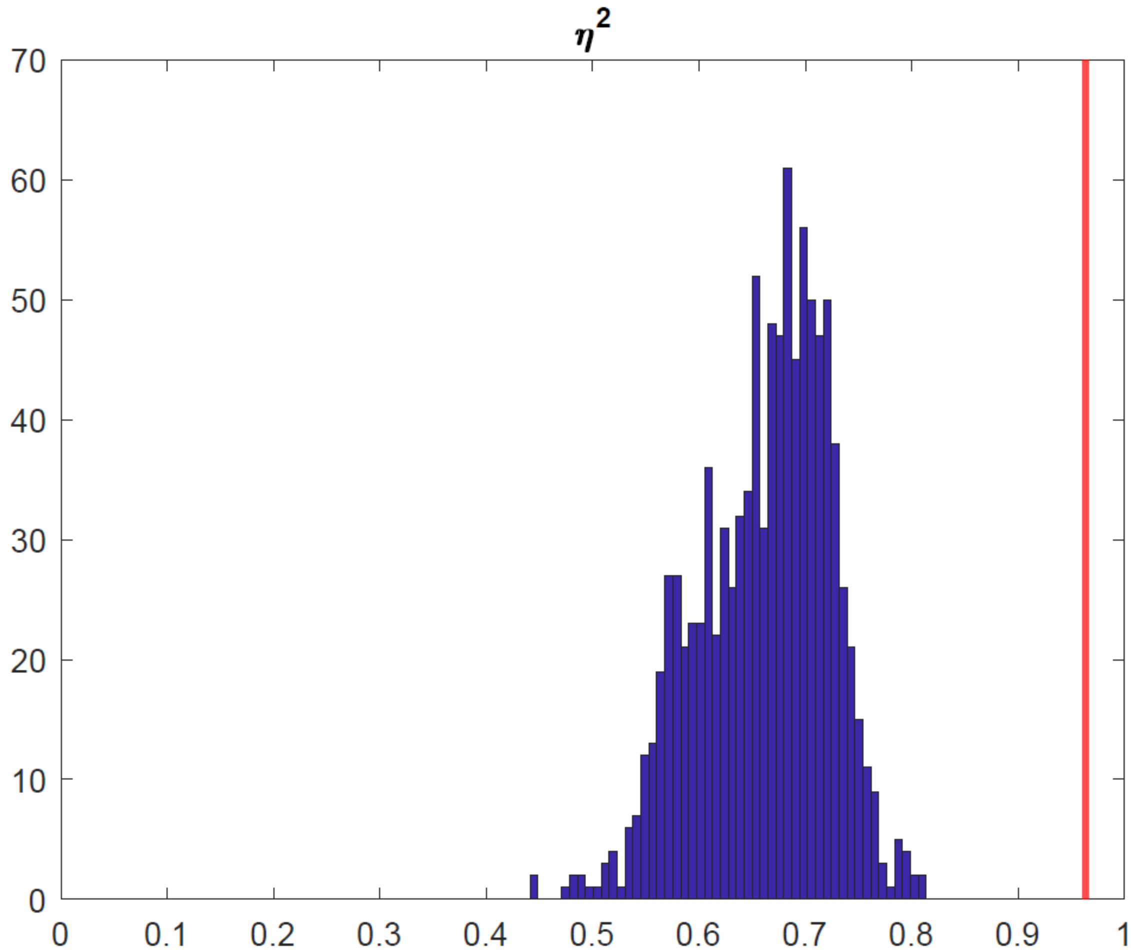
Notes: This figure compares the cumulative exit rate of startups in CompNet (pink bars) and Eurostat (blue bars). CompNet and Eurostat data are matched based on the startup cohort and age group. The x-axis depicts *Startup age*, which is the number of years a startup has been active. *Exit rate* is the average exit rate over all cohorts for each startup age group. France does not appear as Eurostat does not report firm entry prior to 2008.

Figure A4. Scree plots



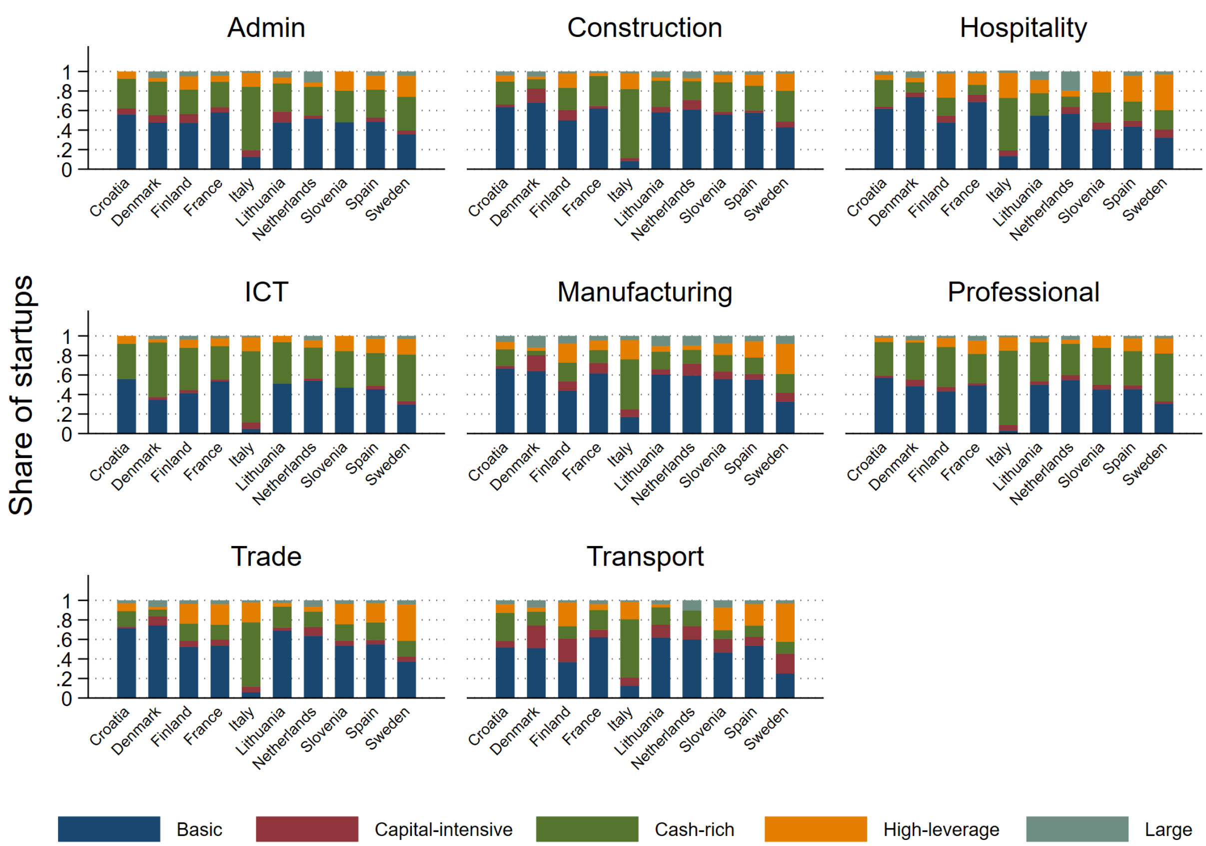
Notes: This figure shows scree plots resulting from the k-means cluster algorithm at the firm-level, for each country in the sample. On the x-axis, k indicates the number of clusters. The η^2 coefficient on the y-axis measures the proportional reduction of the within sum of squares for each cluster solution k compared with the total sum of squares.

Figure A5. Monte Carlo experiment of the meta-clustering



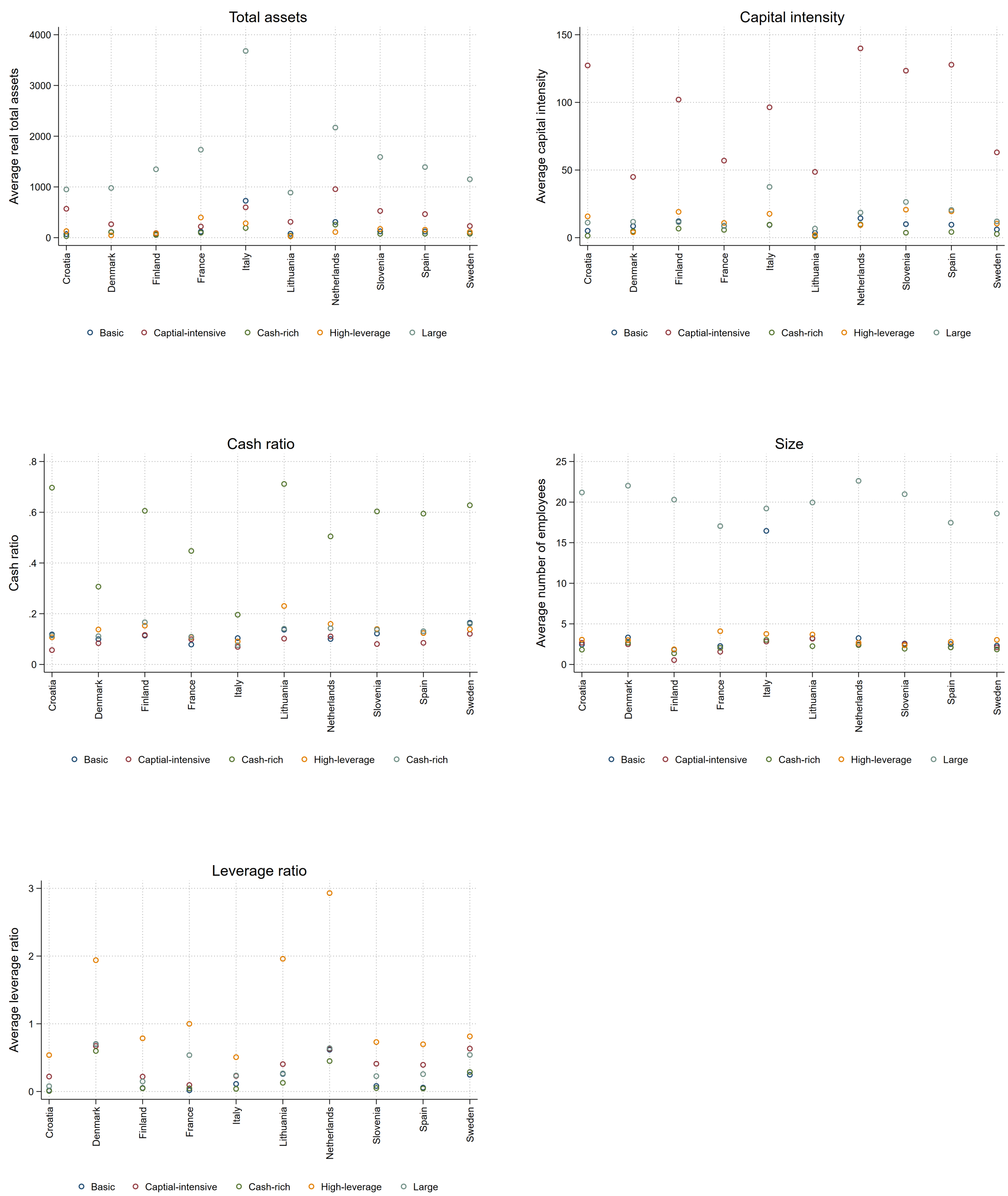
Notes: This histogram summarizes a Monte Carlo experiment consisting of 1,000 random draws for the cluster variables, with means and standard deviations as observed in the data. These draws are i.i.d. so that no clusters exist in the experimental data. Each time η^2 is computed (blue bars). The vertical red line indicates the true η^2 statistic based on the actual data.

Figure A6. Distribution of startup type by industry and by country



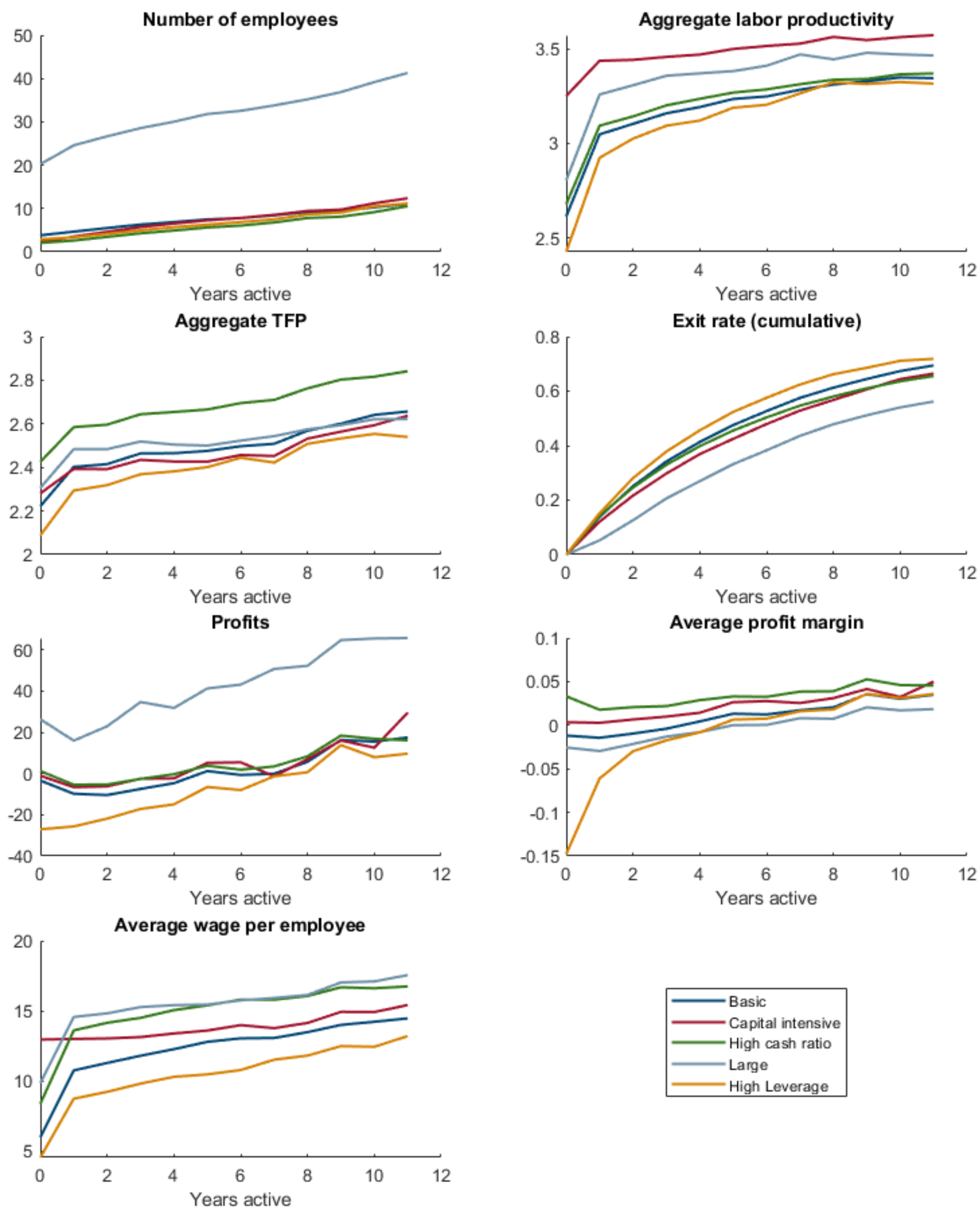
Notes: This figure presents the distribution of the startup population for individual one-digit NACE Rev.2 industries and countries across the five startup types. Shares are averaged over all startup cohorts.

Figure A7. Startup characteristics at the time of firm entry, by type and country



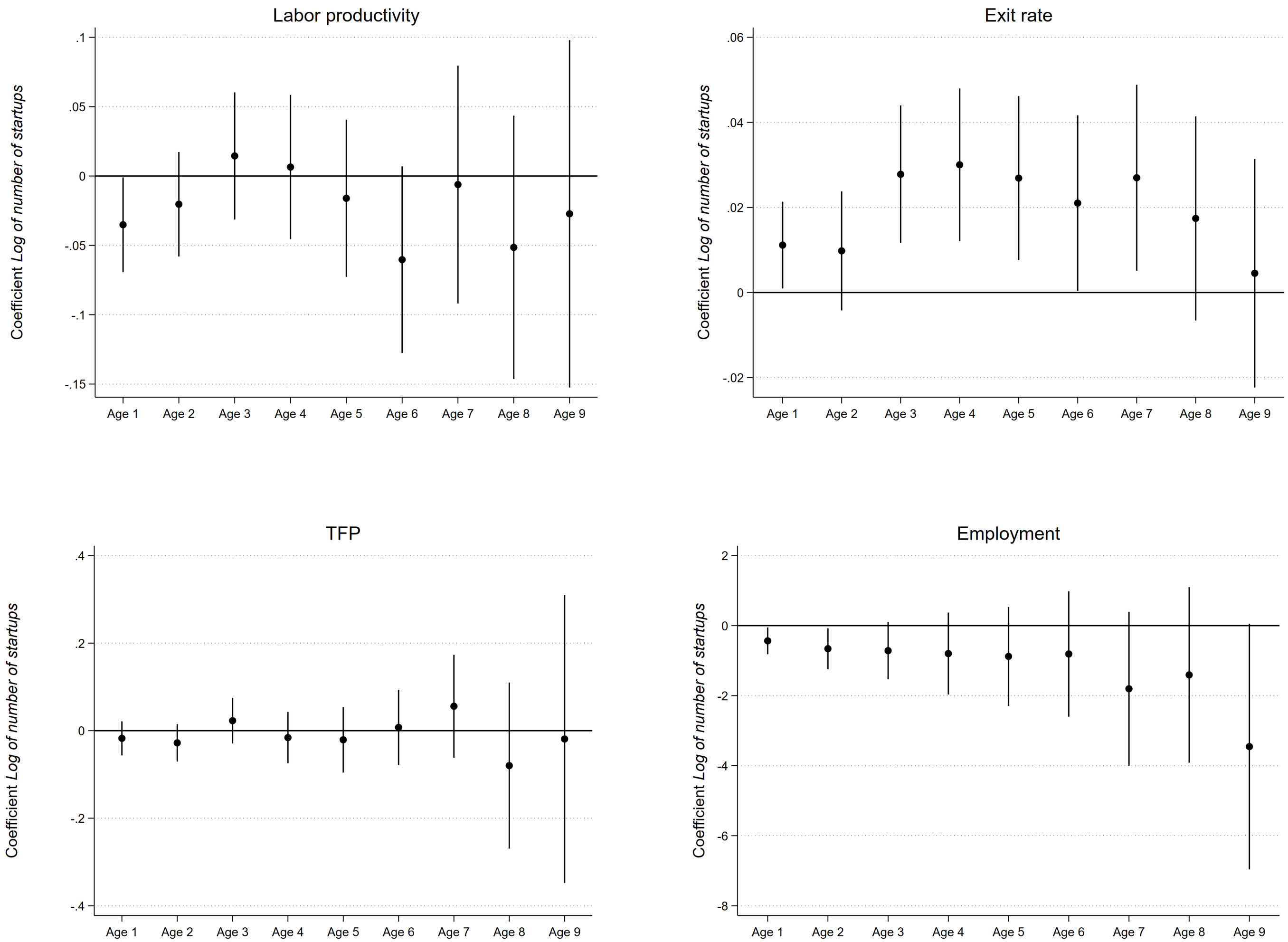
Notes: This figure presents the country-level mean of the five cluster variables for the five startup types in the year of firm entry.

Figure A8. Life-cycle profiles used in the policy experiment



Notes: These charts summarize the development over time of the five startup types in terms of key outcomes. The results are based on panel regressions that include country, cohort, and industry fixed effects.

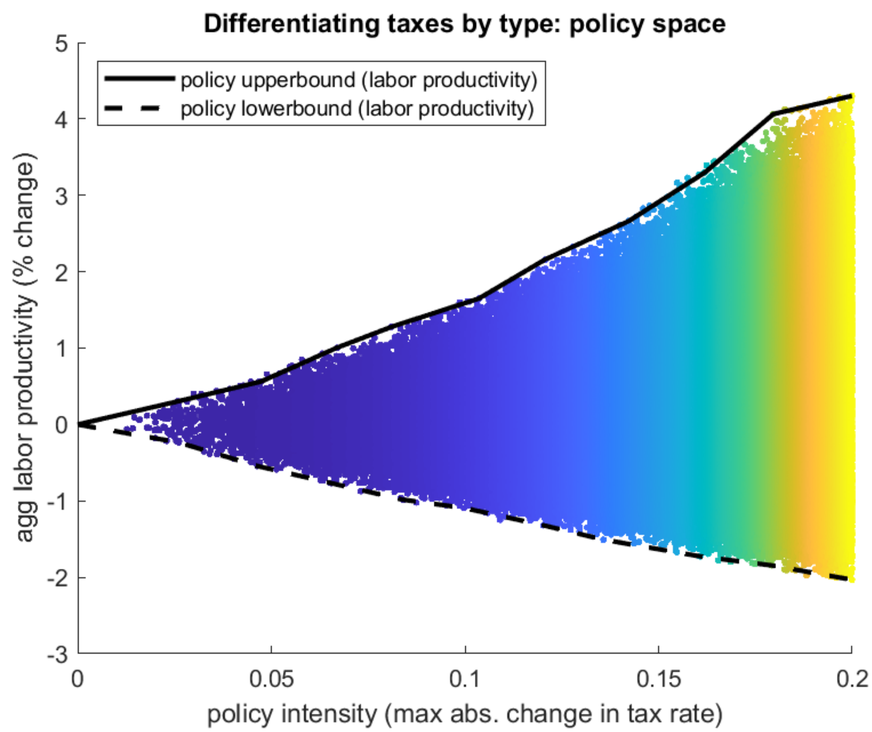
Figure A9. Selection at entry: Number of startups in a cohort and performance later in life



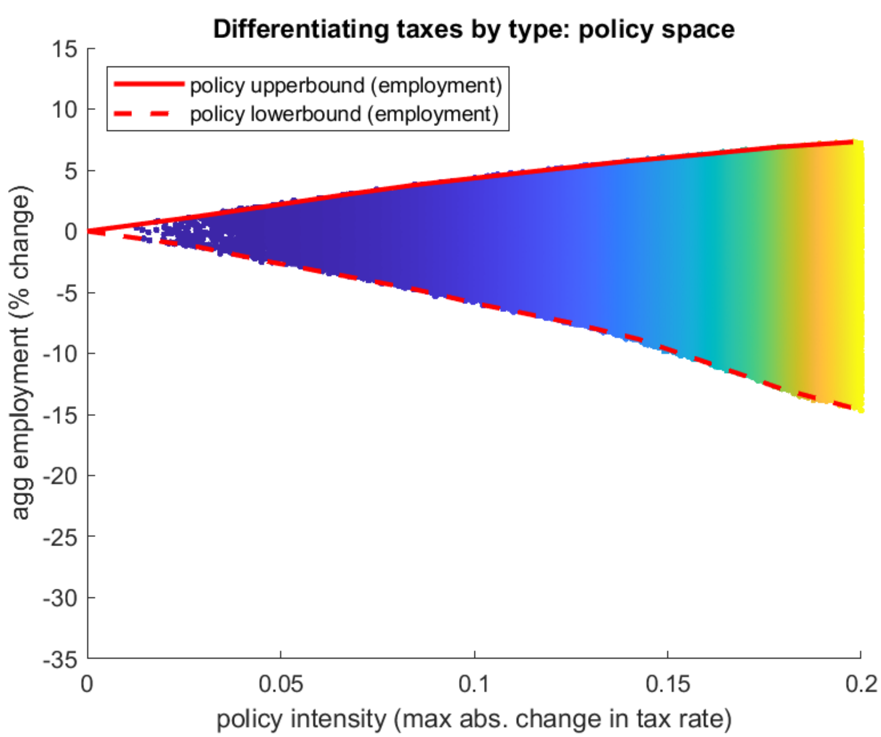
Notes: This figure summarizes OLS regressions where the dependent variable is indicated in the figure titles. *Exit rate* is the cumulative exit rate defined as 1 minus the ratio of number of startups that survived until t divided by the number of startups in *t-0*. Each dot corresponds to a partitioned regression for all startups of a particular age, as indicated on the x-axis, with interactive fixed effects for industry $\times$ startup type $\times$ country; industry $\times$ country $\times$ cohort; startup type $\times$ country $\times$ cohort; and industry $\times$ startup type $\times$ cohort. The regressions are at the one-digit NACE Rev. 2 industry level. Whiskers indicate 95 percent confidence intervals.

Figure A10. Policy experiment with equilibrium adjustment: Tax differentiation and aggregate labor productivity of, and employment within, young firms

Panel A



Panel B



Notes: This figure summarizes the policy experiment allowing for equilibrium adjustment in the labor market. Panel A shows the policy space for aggregate labor productivity. The horizontal axis measures the intensity of the potential policy change as the maximum absolute change in the tax rate. Warmer colors indicate stronger corporate tax rate differentiation. The solid line plots the "policy upper bound": the largest possible increase in aggregate labor productivity given a certain policy intensity. Similarly, Panel B plots the policy space for aggregate employment.

Table A1. Sample composition

Country	Sample period	Number of startups
Croatia	2003-2019	64,760
Denmark	2002-2018	114,195
Finland	2000-2019	126,554
France	2005-2007	210,033
Italy	2007-2018	322,893
Lithuania	2001-2017	47,322
Netherlands	2008-2018	63,729
Slovenia	2006-2019	23,435
Spain	2009-2018	236,192
Sweden	2004-2019	136,376
Total		*1,345,489*

Notes: This table shows the sample composition of the full panel of startups.

Table A2. Variable definitions

Variable	Definition
Capital intensity	Average ratio of real capital stock to the number of employees
Cash ratio	Average cash to total assets ratio
Employment	Average number of employees
Exit probability	1 minus the ratio of number of firms that survived until t divided by the number of startups at $t=0$
Labor productivity	Logarithm of average labor productivity defined as real value-added divided by number of employees
Leverage ratio	Average ratio of debt to total assets
Profit margin	Average ratio of operating profit (Earnings Before Interest and Tax (EBIT)) to revenue
Real total assets	Average real total assets (thousands of euros)
TFP	Average total factor productivity based on a GMM estimation following Ackerberg, Caves and Frazer (2015) and assuming a Cobb–Douglas production function
Wage per employee	Average wage per employee

Notes: All monetary variables are PPP-adjusted.