High-growth firms and misallocation in low-income countries: evidence from Côte d'Ivoire*

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Abstract – Recent research suggests that pervasive market distortions in developing economies hold back employment growth by altering the functioning of products and factors markets. In this paper, we formally study this conjecture based on a unique census-based longitudinal firm-level dataset that covers the Ivorian economy between 2003 and 2012. We find that firm-level performance measures like the growth rate of employment largely reflects distortionary idiosyncrasies. Hypothetically reallocating resources to equalize marginal products across firms both increases the prevalence of high-growth firms and alters the composition of the high-growth pool, as more than three quarters of observed high-growth events arise from implicit distortionary subsidies. Moreover, the divergence of observed and efficient (hypothetical) growth paths becomes more pronounced over the life cycle. This fundamentally questions development policies that target firms based on age or size.
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1 Introduction

Firms that manage to expand at a substantially higher rate than the typical business have been shown to contribute disproportionately to employment growth. Given the recurring failure of low-income countries to generate wage employment for their population, the fostering of the so-called high-growth firms (HGF) looms high on the international development agenda. Yet, recent research suggests that pervasive market distortions in developing economies hold back employment growth by altering the functioning of products and factors markets. This fundamentally questions policies that target firms based on performance measures resulting from factor allocation such as the growth rate of firm-level employment.

In this paper, we formally study this conjecture based on a unique census-based longitudinal firm-level dataset that covers the Ivorian economy between 2003 and 2012.[1] We begin by documenting the high-growth phenomenon in Côte d'Ivoire relative to the empirical regularities identified in developed economies. We then connect this evidence to the literature on firm-level idiosyncratic distortions and assess the extent to which the resulting resource misallocation alters the prevalence and characteristics of HGF in Côte d'Ivoire.

We find that, contrary to the prior about firm growth in a converging low-income country, HGF are not more prevalent in Côte d'Ivoire than in advanced economies. However, eliminating output and factors distortions would create a two- to three-fold increase in the number of HGF. Moreover, it would significantly alter the composition of the fast-growth pool, as more than three quarters of observed high-growth events arise from implicit distortionary subsidies.

Although extremely relevant given the highly skewed distribution of firm-level employment growth, the high-growth phenomenon has been understudied in developing countries due to the unavailability of suitable data. Against this background, and to the best of our knowledge, the census nature of our data enables us to conduct the first systematic investigation into high growth in sub-Saharan Africa in a way that is directly comparable to the existing literature.[2]

Our analysis shows that, from a qualitative perspective, the empirical regu-

[1] This data has only been used in two papers. In Cirera et al. (2017), it is used to quantify the extent of misallocation in Ivorian manufacturing, together with Ethiopia, Ghana and Kenya. The same authors exploit the fact that the panel spans several conflicts periods to study the link between political instability and misallocation (2016). The data in Klapper et al. (2013) comes from the same source but covers the years 1998-2003, while Klapper and Richmond (2011) use the 1977-1997 data, before the the Institut National de la Statistique modernized the registry of enterprises of the modern sector.

[2] Mamburu's (2017) paper on identifying HGF in South Africa is the only other example of study of the high-growth phenomenon in sub-Saharan Africa based on comprehensive data, albeit with the essentially different purpose of assessing the consequences of using different definitions.

larities identified about HGF in advanced economies essentially hold for Côte d'Ivoire. In particular, we confirm the robustness of the following seven stylized facts: (i) the distribution of growth rates is tent-shaped; (ii) HGF account for a disproportionate share of employment creation; (iii) HGF are younger than average; (iv) they are present in most industries; (v) high-growth episodes are not persistent;[3] (vi) firm-level characteristics are poor predictors of high-growth status; and (vii) the way HGF are defined matters.

A priori, these results constitute a puzzle. While advanced economies lie at the technological frontier by definition and essentially rely on productivity-enhancing innovation for growth, one expects the convergence process to afford cheap growth opportunities in developing economies. As a logical implication, the fast-grow phenomenon should be more marked in Côte d'Ivoire than in developed countries. On that premiss, we contend that ubiquitous market distortions in poor countries prevent firms from reallocating input towards more productive use and "reaping the low-hanging fruits".

In order to inform our conjecture, we rely on the well-known accounting framework put forward by Hsieh and Klenow (2009, HK hereafter) to study the impact of resource misallocation on the high-growth phenomenon. This framework has been used extensively to explain differences in total factor productivity based on within-industry dispersion in marginal revenue products.[4] Perhaps surprisingly, however, the potential to identify those firms that are dampened by distortions has not received much attention.[5] Yet, in a economic environment characterized by pervasive market distortions, development policies focusing solely on employment growth are likely to worsen misallocation by fostering firms of which the fundamentals do not warrant such interventions.

We bridge this gap in the literature by considering the hypothetical situation in which resources are allocated efficiently. Specifically, we rely on the HK decomposition to construct counterfactual firm sizes that would prevail if inputs were allocated such that marginal revenue products are equalized across firms within an industry. Based on these optimal firm sizes in repeated distorsion-free equilibriums, we identify the subset of firms that would experience high growth in such counterfactual economy. It enables us to compare these counterfactual HGF to the actual ones. Our exercise shows that the distribution of efficient growth rates is much thicker than the observed one, indicating that distortions are an impediment to extreme growth events. It also shows that more than

[3] In a significant departure from the advanced economies experience, where HGF are likely to experience moderate growth in the subsequent period, HGF in Côte d'Ivoire are as likely to exit as their non-high-growth counterparts.

[4] The HK framework has been applied to a wide range of countries, datasets and periods; relevant to our paper, the case of Côte d'Ivoire has been studied by Cirera et al. (2017).

[5] We are only aware of the work by Calligaris (2015), who applies the HK procedure to different firms subsets based on characteristics such as age, location and technological intensity in order to link them to the extent of misallocation.

80 percent of observed HGF would not have that status absent the distortions, while almost 25 percent of non-high-growth firms would experience high growth in the counterfactual economy. Moreover, distortions seem to get worse over the lifecycle, as counterfactual HGF prevalence increases with age while actual HGF prevalence decreases.

Our analysis of the HGF-distortions nexus has far-reaching implications for job creation policies in Côte d'Ivoire, and in low-income countries in general to the extent that they exhibit similar levels of resource misallocation. Indeed, our results indicate that firm-level performance measures like size and growth largely reflects distortionary idiosyncrasies rather than productivity. Moreover, the divergence of observed and efficient growth paths becomes more pronounced over the life cycle. Therefore, this paper suggests that the widespread interest in targeting specific groups of firms based on size or age is misguided, and that the key to tackling low job growth lies in broadly alleviating allocative distortions.

The remainder of the paper is organized as follows. Section 2 provides background information on Côte d'Ivoire, as well as the relevant literature on HGF and on resource misallocation. In section 3, we present the data, while we discuss the identification of HGF in section 4. Section 5 contains our analysis of the high-growth phenomenon in Côte d'Ivoire, which we compare to the evidence from developed economies. We finally describe our appropriation of the HK framework and lay out our findings based on our counterfactual exercise in section 6.

2 Background

2.1 Côte d'Ivoire

Our study covers a period characterized by protracted political instability in Côte d'Ivoire, as the country experienced two major civil wars in 2003-2004 and in 2010-2011. An African success story until the dramatic drop in the international prices of cocoa and other major Ivorian exports in the late seventies, the country's modest macroeconomic performances at the end of a cycle of structural adjustment programs suffered from these conflicts (see Cirera et al., 2016, for details). Nevertheless, the country remains one of the largest economies in Western Africa and the biggest player of the Union Économique et Monétaire Ouest-Africaine.

2.2 High-growth firms

Employment growth is one of policymakers' most pressing concern. Understanding the sources and the dynamics of structural job creation therefore attracts considerable attention. With that respect, the extensive literature that ensued

from Birch's (1979) paradigm-changing contribution has identified a number of stylized facts regarding the composition of job growth. The most robust of them can be stated baldly as follows: a small number of relatively young firms account for most new jobs. In the United Kingdom for example, half the new jobs created over the period 2002-2008 are attributable to only six percent of all firms (NESTA, 2009); in the United States, two to three percent of all firms account for almost all of the private sector employment growth between 2002 and 2006 (Acs et al., 2008); in Sweden, six percent of firms generated 42 percent of the jobs between 2005 and 2008 (Daunfeldt et al., 2015); and there are many more documented instances of the disproportionate contribution of the so-called high growth firms (HGF) to overall employment growth.[6] Such findings have been extremely influential in shaping public policies aimed at fostering employment. Famously labelled 'gazelles', HGF have become policymakers' champions. Growth accelerators and other business incubation initiatives have now become a central tenet of economic policies that channel tremendous public sector support (OECD, 2013). As an example, often quoted for its illustrative power, the United Kingdom spends more taxpayers' money on entrepreneurship support than on the police force or universities (Storey, 2008).

No matter how important these few young firms are for employment creation, the inexorable evidence is not all entrepreneurial firms are high-growth. Most new firms do not grow, and the death rate amongst entrants is high.[7] Therefore, beyond the essentially tautological assertion that HGF create most new jobs, an important research agenda focuses on identifying the intrinsic attributes of businesses that disproportionately contribute to economic growth. Implicit is the idea that a better grasp of such fondamental characteristics as the size, age, ownership structure, sectoral and geographical distribution of HGF would enable policy makers to design public policies aimed at fostering their develpment.[8] With that respect, the extensive literature on HGF has identified a number of robust empirical regularities. However, these regularities exclusively rely on the experience from developed economies. The question of the extent to which they apply to developing economies remains an open one.

The economic environment in developing countries features a number of specificities that potentially qualify these empirical regularities about high growth that have been identified in developed countries. An important element is the fact that the typical firm in developing countries consists of its owner only. It constitutes a significant departure from developed countries like the United

[6] See the authoritative survey about HGF as job creators by Henrekson and Johansson (2010), who review twenty studies covering ten different OECD countries and data from between 1977 and 2006.

[7] This strikingly contrasts with the common glorification of entrepreneurship. On the positive interpretation of entrepreneurship research and the frequent amalgam of HGF and entrepreneurship, see Nightingale and Coad (2014).

[8] Against this idea, recent works indicate that high growth shows very little persistence and suggest that high-growth events are random. See eg. Bianchini et al. (2017).

States, where the modal value of firm size is 45 workers (Hsieh and Klenow, 2014). As such, it raises obvious questions with respect to the very meaning of high employment growth at the firm level. Beyond this first-order difference, there also exists second-order size differences related to the distribution of firm employment. Although it is as highly dispersed in developing countries as it is in developed countries, the skewness differs significantly. Some authors have put forward the hypothesis of a missing middle, as a number of impediment to growth like red tape or market imperfections kick in at a very small size. This prevents small firms to reach an efficient scale of production, while the largest firms are influential enough to obtain special treatment (Tybout, 2000).[9] Related, it is often argued that firm life cycle is fundamentally different in developing countries. Indeed, contrary to developed countries where surviving entrants typically converge towards the industry average, developing countries seem to exhibit a divergence between the top and the bottom of the distribution, as small businesses struggle along while the biggest firms contribute disproportionally to employment growth (Van Biesebroeck, 2005).

2.3 Resource misallocation

Pervasive resources misallocation consititutes another key characteristic of low-income countries in general, and sub-Saharan Africa in particular. Restuccia and Rogerson (2008) famously argued that at least part of the gap in total factor productivity of manufacturing between developed and developing economies is attributable to the misallocation of resources across firms. From their seminal empirical approach that enables them to measure misallocation, Hsieh and Klenow (2009) conclude that aggregate productivity would be 30 to 60 percent higher in China and India if inputs were allocated as efficiently as they are in the United States. The HK strategy for estimating the extent of misallocation as been use in the context of other countries. Of particular interest to this paper, Cirera et al. (2017) study the case of Côte d'Ivoire and show that distortions tax TFP by around 30 percent in 2012.

At the microeconomic level, resource misallocation directly affects the distribution of firm size and, in a dynamic setting, the distribution of growth rates. Input misallocation implies that some firms grow further than their efficient size, while others are hindered in their growth path. As a consequence, the fastest-growing firms need not be the ones that would thrive based on their idiosyncratic productivity level, and the observed characteristics of HGF in developing economies need not be related to superior job creation potential. Given the overwhelming evidence of severe resource misallocation in developing economies (e.g. Cirera et al., 2017; Busso et al., 2013), assessing how idiosyncratic distor-

[9] Hsieh and Olken (2014) question the very existence of a 'missing middle' phenomenon, and argue that big firms are missing as well.

tions affect growth patterns is of first-order importance.

3 Data

Our data comes from the confidential registry of enterprises of the modern sector maintained by the Institut National de la Statistique (INS). It consists of yearly balance sheets and income statements reported to various government entities, including the tax administration (Direction Générale des Impôts) and the central bank system of West African countries (Banque Centrale des Etats Ouest-Africains), and covers all registered firms in Côte d'Ivoire. Besides firms characteristics such as location, year of establishment, legal form and industry, it encompasses detailed information on revenue, employment, labor and intermediate input costs, and book value of assets. The data comprises 60,558 firm-year observations, corresponding to 24,573 unique firms for the period 2003-2012.

Because the data is census-based, it offers a comprehensive view of the entire formal economy in Côte d'Ivoire, covering all industries and all sizes. However, it suffers two major limitations that we attenuate by parsimoniously cleaning the raw data. The first is linked to the protracted political instability that characterizes the period under consideration. Côte d'Ivoire has experienced two major civil conflicts, in 2003-2004 and in 2010-2011, with a "no-war-no-peace" deadlock in-between. Therefore, both de jure and de facto legal requirements regarding firm reporting varied over the period and, as a consequence, the data presents a number of one-year gaps in otherwise complete panels. The data features 862 firm-year observations with missing employment value, corresponding to no fewer than 827 panels. Because this is especially detrimental to studying prolonged growth spells, we impute employment data where we believe the gap is a consequence of change in reporting rather than exit and subsequent entry; specifically, we interpolate missing employment values whenever the available information leaves no doubt that the firm kept operating during the data gap. Out of 862 missing employment values, 458 are imputed this way, and the others are dropped.

The second major limitation of the data is related to the widespread prevalence of very small (even though registred) businesses and subsistence self-employment in sub-Saharan Africa. Appropriately accounting for the phenomenon is relevant, because these firms are both numerous and unlikely to experience high-growth spells; hence they constitute a significant part of the non-high-growth group in comparison of which high-growth firms are studied. We assume that firms reporting zero employment but positive wages correspond to self-employment; for these we replace the zeros by one to reflect the fact that they actually constitute employment. At this point, we miss out the remaining non-employment firms and are left with 54,644 firm-year observations, corresponding to 22,157 panels. Table 1 reports the descriptive statistics for our data.

Table 1: Firm-level descriptive statistics, Côte d'Ivoire, 2003-2012.

	All firms		Manufacturing		HK sample	
	mean	median	mean	median	mean	median
Age (year)	8.3	5	12	7	16	12
Size (workers)	47	6	122	18	218	48
Sales (million FCFA)	1,935	95	5,458	201	7,265	741
Wages (million FCFA)	118	7.6	270	25	481	95
Capital (million FCFA)	407	3.4	920	26	1,467	116
Value added (million FCFA)	288	13	675	33	1,282	168
Exporter (dummy)	.025		.15		.23	
Abidjan (dummy)	.86		.89		.89	
High-technology (dummy)	.0037		.031		.043	
Knowledge-intensive (dummy)	.086					
Observations	54,644		6,469		3,096	

Some missing values for sales, capital and value added

Source: microdata obtained from the Institut National de la Statistique.

Finally, our misallocation analysis raises a number of further data constraints. In line with the literature, we restrict the counterfactual exercise to the manufacturing sector, as the assumptions on the production technology and factors shares reduce its relevance for the services sector. As a consequence, this part of the analysis is carried out on a much smaller population of 6,469 firm-year observation, corresponding to 2,247 unique firms. The exercise also requires consequent data on input costs and assets value. Moreover, given the usual profit maximization hypothesis, the HK framework does not accommodate negative value added, which occurs frequently in our Côte d'Ivoire case. This reduces further the data we can use for our analysis to 3,096 firm-years, corresponding to 897 panels. Expectedly, the sample obtained features significantly different characteristics from the manufacturing population, with the firms in the HK sample being essentially bigger, as table 1 shows.

4 HGF identification

In their taxonomy of HGF, Delmar and Davidsson (1998) identify four elements to be combined in order to define high growth, namely (i) the growth indicator, (ii) the growth measurement, (iii) the duration of the growth spell and (iv) the process of growth. Because different choices with respect to these elements can affect which firms are selected as HGF, we briefly discuss the issues relevant to our analysis.

Employment and sales are by far the most used growth indicators in the HGF literature. Although only modestly correlated, they produce similar results in terms of economic contribution of HGF (Daunfeldt et al., 2014). The measure-

ment of growth, however, makes an important difference (see Almus, 2002); in particular, relative growth measures tend to select smaller firms than absolute measures. For this reason, the literature has resorted to mixed measures in order to quantify employment growth. The most common of these measures are the Birch index, which multiplies relative growth by absolute growth, and the combination of a growth and a size requirements. Regarding the growth horizon, we follow most studies and calculate growth rates over a few years in order to attenuate one-off changes and statistical noise. Finally, our data does not allow us to differentiate the process of growth.

In this paper, we focus on employment rather than sales as a growth indicator. This choice is dictated by the sub-Saharan context: wage employment is often correlated with desirable economic outcomes at the household level (Banerjee and Duflo, 2008) whereas, from a macroeconomic perspective, it is traditionaly associated with the structural transformation process that moves resources from non-market agriculture to more productive sectors (Lewis, 1954). Regarding the measurement of growth, we prefer mixed measures because they prevent the analysis from being polluted by economically irrelevant changes among small firms, of which there is typically any number in developing economies. Therefore, we choose as our main definition the one recommended by the OECD and define HGF as firms that experience a compound annualized growth rate of 20 percent over three years, with a base size of minimum ten employees (OECD, 2007). Formally, this writes

$$\log \frac{L_{is}(t)}{L_{is}(t-3)} \geq 3 \log 1.20 \quad \bigcap \quad L_{is}(t-3) \geq 10 \tag{1}$$

where $L_{is}(t)$ stands for time t employment at firm i in sector s.

We are aware that this definition excludes by construction the overwhelming majority of firms that either are not three-years old or employ fewer than ten workers. This is not specific to the Côte d'Ivoire case: Daunfeldt et al. (2015) show that the OECD definition excludes about 95 percent of surviving firms and 40 percent of new jobs in Sweden between 2005 and 2008 period. In our data, more than 65 percent of firm-year observations have fewer than ten workers, while almost 80 percent do not survive three years over the relevant period; together, this implies that the OECD definition excludes about 85 percent of the population.[10]

Table 2 presents the year distribution of firms and HGF for the entire population as well as for each of our manufacturing subsets. To account for the fact that most businesses are very short-lived, we also present the count of eligible firms,

[10] This figure is higher than in Sweden because our data only covers formal firms, which are typically much bigger and less likely to exit than the average business in low-income countries.

Table 2: HGF prevalence, Côte d'Ivoire, 2006-2012.

	All firms			Manufacturing			HK sample		
	Pop.	Elig.	HGF	Pop.	Elig.	HGF	Pop.	Elig.	HGF
2006	3,268	929	67	463	242	13	268	165	11
		.2843	*.0721*		*.5227*	*.0537*		*.6157*	*.0667*
2007	3,660	903	78	497	235	16	281	162	11
		.2467	*.0864*		*.4728*	*.0681*		*.5765*	*.0679*
2008	4,451	941	95	540	233	24	276	164	16
		.2114	*.1010*		*.4315*	*.1030*		*.5942*	*.0976*
2009	5,313	986	109	663	239	26	310	168	22
		.1856	*.1105*		*.3605*	*.1088*		*.5419*	*.1310*
2010	7,545	935	95	791	219	22	333	161	14
		.1239	*.1016*		*.2769*	*.1005*		*.4835*	*.0870*
2011	9,397	1,085	79	950	234	19	388	160	15
		.1155	*.0728*		*.2463*	*.0812*		*.4124*	*.0938*
2012	12,090	1,183	126	1,189	253	36	447	167	20
		.0978	*.1065*		*.2128*	*.1423*		*.3736*	*.1198*
Total	45,724	6,962	649	5,093	1,655	156	2,303	1,147	109
		.1523	*.0932*		*.3250*	*.0943*		*.4980*	*.0950*

Firm count; relevant share in italics
Share of eligible firms in the population; share of HGF in the eligible subset

Source: microdata obtained from the Institut National de la Statistique.

that is, firms that survive at least three years and are thus eligible for high-growth status. The data shows a steady increases in the number of firms over the period, from around three thousand in 2006 to twelve thousand in 2012. The phenomenon is significantly less marked for manufacturing and the HK sample, confirming that these firms are essentially different from the average business in the population. Strikingly, the eligible and HGF counts hardly increase over the period, implying that the dramatic increase of in the number of firms mostly comes from businesses that exit the market soon after entry.

In terms of prevalence, the essential insight is that the share of HGF in the eligible subset is stable at around ten percent across our three sets (all firms, manufacturing, HK sample). This hides significant dispersion across subsets when looking at the share of HGF in the population, given the differences in eligibility emphasized above: HGF prevalence in the entire population is slightly below one and a half percent, while it reaches three percent for the manufacturing population and five percent for the HK population. This calls for caution when comparing prevalence across structurally different samples.

Finally, although we favor the OECD concept, we sometimes resort to other definitions depending on the object of analysis and the methodological constraints we face. For the purpose of assessing robustness, we also look at distribution-based definitions, specifically the highest five percent of the growth rate distribution and of the Birch index distribution over a three-year period.[11] The number of HGF based on these two criteria is very comparable to the one obtained using the OECD definition, hence we do not report the associated firm counts. Constraints on the use of specific definitions arising from the HK methodology are discussed in section 6.2.

5 Stylized facts compared

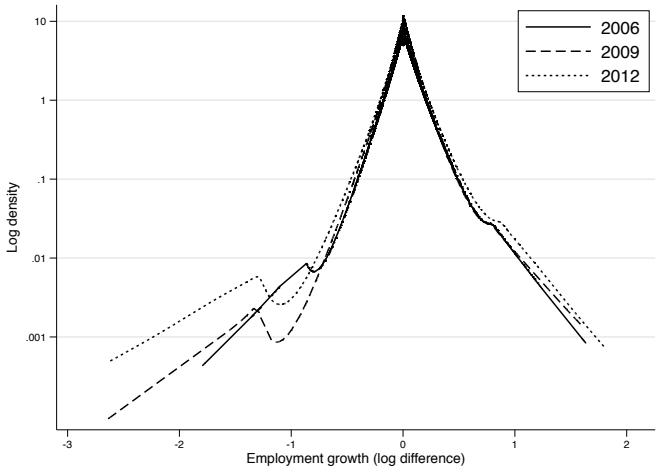
In the introduction to the special issue of *Industrial and Corporate Change* on HGF, Coad et al. (2014) identify seven empirical regularities about the high growth phenomenon that are robust enough across studies to be considered as stylized facts. This set of findings is, however, based on the experience of advanced economies. In this section, we revisit the stylized facts in the context of the Ivorian economy. To the best of our knowledge, it constitutes the first systematic attempt at investigating HGF in sub-Saharan Africa in a way that is comparable to the existing literature.

[11] The respective conditions are $g_{is}(t) > \inf\{\bar{g} : \Pr\left(g_{is}(t) < \bar{g}\right) > .95\}$ where $g_{is}(t) = {}^{L_{is}(t)}/_{L_{is}(t-3)}$ is the three-year growth rate, and $b_{is}(t) > \inf\{\bar{b} : \Pr\left(b_{is}(t) < \bar{b}\right) > .95\}$ where $b_{is}(t) = \left(L_{is}(t) - L_{is}(t-3)\right) {}^{L_{is}(t)}/_{L_{is}(t-3)}$ is the Birch index.

5.1 Distribution of growth rates

The distribution of growth rates typically display heavy tails in developed countries. In their seminal contribution, Stanley et al. (1996) show that the density of growth rates in US manufacturing exhibits a "tent-shaped" form, suggesting that the distribution is exponential, rather than Gaussian as Gibrat's law implies. Ensuing research suggests that growth rates follow a Laplace distribution (e.g. Bottazzi and Secchi (2006);Coad (2010); Bottazzi et al. (2011)).[12] [13] This shape for the distribution of growth rates indicates that most firms do not grow at all, while the tails of the distribution account for the overwhelming part of the dynamics. The corollary is that a small group of firms account for most of aggregate growth, a fact to which we come back in the next subsection. Incidentally, the high density of extreme growth events constitutes the raison d'être for research on HGF.

Figure 1: Distribution of firm growth rates, Côte d'Ivoire, 2006, 2009 and 2012.



Source: microdata obtained from the Institut National de la Statistique.

How does firm-level growth in the Ivorian economy compare with its more advanced counterparts? Figure 1 plots the (smoothed) density of growth rates of

[12] The Laplace distribution is also referred to as the double exponential, because its plot consists of the exponential function and its orthogonal symmetric transposition juxtaposed along the vertical axis, hence the characteristic tent shape.

[13] Halvarsson (2013) argues that the growth rate distribution of incorporated Swedish firms becomes a power law far in the right tail.

employment on the log-log scale for the years 2006, 2009 and 2012.[14] Straightforward inspection reveals that growth rates are about as dispersed in Côte d'Ivoire as they are in Italy or France (see e.g. Bottazzi et al., 2011, figure 4). The characteristic tent shape is striking; as in developed countries, a lot of probability mass is located around zero. Overall, the distribution of growth rates in Côte d'Ivoire ressembles the one observed in advanced economies.

5.2 Composition of growth

A small number of HGF accounts for most job creation in developed countries at any given point in time. This is an obvious corollary of the heavy-tailed distribution of growth rates. This disproportionate contribution to employment creation is undoubtedly both the most researched and the most robust finding about HGF. Amongst the most cited items in the field are Birch and Medoff (1994), who conclude that four percent of firms account for 60 percent of new jobs in the United States between 1988 and 1992, and Storey (1994), who estimates that four percent of firms are responsible for half of new jobs in the United Kingdom. This empirical regularity has been observed in many different countries, with different sampling of firm populations and different time frames. The authoritative survey by Henrekson and Johansson (2010) reviews the abounding evidence of HGF as job creators based on studies covering ten different OECD countries and data from 1977 to 2006.

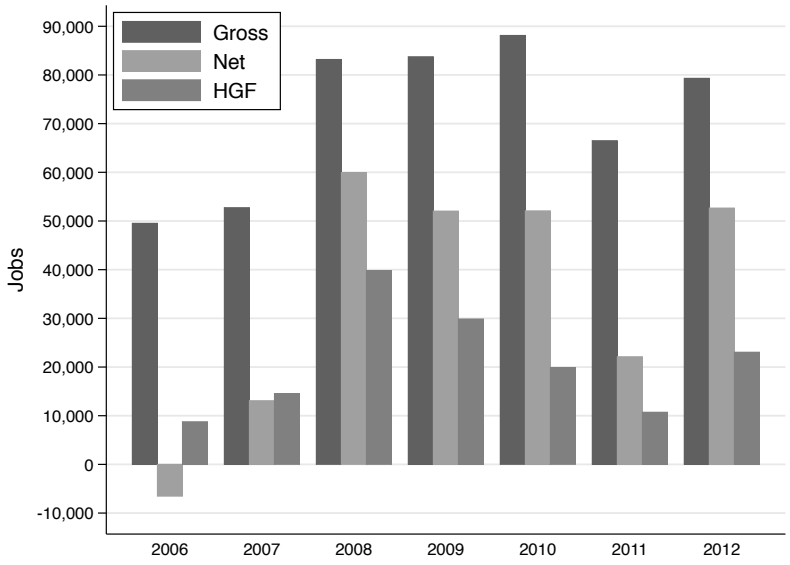
Figure 2 reports the composition of annual job creation for each three-year period between 2003 and 2012. However, the volatility of economic activity in Côte d'Ivoire emphasized above calls for caution, as it makes comparisons with the existing literature misleading; in particular, high exit rates make the picture very different depending on wether one looks at gross or net job creation, as exit offsets an important fraction of HGF job creation some years.[15] For this reason, it is relevant to assess HGF contribution to job growth relative to gross job creation ass well. The two measures are reported together with job creation by HGF identified based on the OECD definition.

The figure indicates that the magnitude of the contribution of HGF to job creation is essentially comparable to the advanced economies experience if we abstract from the high entry and exit rates. We observe a disproportionate job creation by a few fast-growing firms: overall, the contribution of one to two percent of firms to net job creation ranges from 40 to one hundred percent. In terms of share of gross creation, the same firms account for 15 to 50 percent. The basic insight is robust to using our other two definitions; in particular,

[14] Note that the stylized fact holds strictly only if based on growth measured in logarithmic differences, which is just a monotonic transformation of any other relative growth measure.

[15] It is particularly misleading for the periods 2003-2006 and 2004-2007, when HGF created more jobs than the entire economy in net terms.

Figure 2: Composition of three-year job creation, Côte d'Ivoire, 2006-2012.



Source: microdata obtained from the Institut National de la Statistique.

relying on the Birch index only amplifies the phenomenon.

5.3 Age and size

A considerable body of research has focused on the characteristics of HGF in developed economies. Age and size are amongst the most pervasive predictors of high growth in a wide variety of settings, growth indicators and measurement (Delmar et al., 2003). Independently of measurement choices, HGF are younger than the average firm (Daunfeldt et al., 2014). The widely held view that most HGF tend to be small calls for caution, as a non-negligible number of them are actually large (Acs and Mueller, 2008). Haltiwanger et al. (2013) find that there is no systematic relationship between size and growth once age is appropriately controlled for; they argue that the negative correlation between growth and size simply comes from the statistical fallacy associated with most young firms being small.

Table 3 presents unconditional age and size mean differences between HGF and non-HGF, and reports standard errors as well as the significance level of a Student's test on mean equality. The mean differences are taken for eligible firms at the beginning of the high-growth spell for each of the three definitions described above. The result depends on the choice of definition, an issue to

Table 3: Age and size unconditional mean difference, Côte d'Ivoire, 2006-2012.

	OECD definition	**Top 5% growth**	**Top 5% Birch**
Age	-5.317***	-6.967***	2.520***
	(0.482)	(0.300)	(0.600)
Base year size	-69.18***	-74.35***	452.4***
	(20.42)	(8.563)	(50.36)
Davis et al. size	48.12	-5.824	620.4***
	(33.08)	(19.74)	(58.33)
Observations	6962	12613	12613

Standard errors in parentheses
Welch's correction for unequal sample size and variance
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: microdata obtained from the Institut National de la Statistique.

which we come back below. Our main definition suggests a pattern in line with the conventional wisdom about HGF: when defined according to the OECD recommendations, HGF seem to be (unconditionaly) younger and smaller than the average firm. However, the evidence on size is less clear-cut when using average size as proposed by Davis et al. (1996) to correct for regression-to-the-mean biases.[16] The insight is essentially the same when looking at the top five percent of firms with the highest growth rate. It is, however, clear-cut different for both age and size when high-growth classification is based on the Birch index. High-Birch firms are both older and bigger than the average firm at the beginning of their high-growth spell. This is arguably an artifact of the Birch index, as it is more sensitive to absolute changes than to relative ones (Hölzl, 2014).

The stylized fact emphasized for developed economies thus arguably holds for Côte d'Ivoire as well. However, an important caveat applies. Out of the 22,159 unique firms in the data, more than 85 percent do not survive more than three years. This extreme exit rate suggests that the life cycle of Ivorian firms is very different from the one observed in developed economies, and calls for caution when comparing firm age differences.

5.4 Industry prevalence

High growth is traditionally understood as the outcome of superior innovative capabilities (see Dennis, 2011). Contrary to the conventional wisdom, however,

[16] We regress high growth status in a linear probability model in subsection 5.6 below. Conditional mean differences are consistent with the evidence presented in this section and confirm the argument by Haltiwanger et al.

the typical HGF in advanced economies is not a high technology firm. They are found in every sector and there does not exist any empirical evidence to back the assertion that HGF are overrepresented in high-tech manufacturing industries (e.g. Acs et al., 2008; Hölzl, 2009; Henrekson and Johansson, 2010). If anything, recent works suggest that HGF prevalence is higher in knowledge-intensive service industries (Daunfeldt et al., 2016).

Table 4: Industry prevalence unconditional mean difference, Côte d'Ivoire, 2006-2012.

	Knowledge intensive	High technology
OECD definition	0.0452	-0.0304
	(0.0402)	(0.0336)
Top 5% growth	0.0124	-0.0286
	(0.0159)	(0.0191)
Top 5% Birch	0.0202	0.0296
	(0.0256)	(0.0441)
Observations	275	275

Standard errors in parentheses
Welch's correction for unequal sample size and variance
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: microdata obtained from the Institut National de la Statistique.

As for developed economies, the Ivorian evidence is essentially inconclusive, as shown in table 4. We use the same classification for knowledge-intensive service industries and for high-technology manufacturing industries as Daunfeldt et al. (2016, table A1).[17] The table reports unconditional mean differences in HGF prevalence between knowledge-intensive industries and the rest (column 1) as well as between high-technology industries and the rest (column 2). Industry-level prevalence is reported at the NAEMA four digits level. No matter the chosen definition, knowledge-intensive service industries show a higher HGF prevalence. The evidence is mixed for high-technology manufacturing industries and depends on the chosen HGF definition; here too, considering high-Birch firms flips the result. It may come from the fact that defining high growth based on the Birch index is biased towards larger firms, as mentioned above, and these large firms are more likely to cover fixed costs associated with high technology. As turns out, however, based on Student's tests there is no significant difference in HGF prevalence for any of the two types of industry.

A number of limitations in the data call for caution, here again. Compared to the data used by studies on developed economies, our data is much smaller in terms of the number of firms, hence the number of HGF. There are relatively few firms by industry when disaggregating the economy at the four digits level,

[17] Specifically, we take ISIC Rev3.1 divisions 59 to 63 and 70 to 73 as knowledge intensive service industries, and divisions 21, 26 and 30 as high technology manufacturing industries.

and there are only 275 NAEMA industries represented in the data at that level of disaggregation. Therefore the variation in industry prevalence of HGF may not carry much information. It is thus likely that belonging to high-tech or knowledge-intensive industries does not have much explanatory power in the case of Côte d'Ivoire.

5.5 High-growth persistence

Most studies on the high-growth phenomenon are static in nature, which questions the relevance of policy implications, especially if growth is mainly driven by (random) demands shocks (see Henderson et al., 2012). More recent works based on longer panels all tend to suggest that sustained high growth is unlikely; specifically, high-growth spells are not persistent over time (Coad, 2007; Coad and Hölzl, 2009; Hölzl, 2014; Daunfeldt and Halvarsson, 2015). The basic insight is that the probability for a HGF to repeat the high-growth event is not different from the probability for any firm to experience a high-growth episod; moreover, persistence seems to depend on the choice of growth measurement. The recent study by Bianchini et al. (2017) into the determinants of persistent high growth in France, Italy and Spain is not conclusive, which vindicates the random growth conjecture.

Table 5: Transition into HGF status, Côte d'Ivoire, 2006 and 2009.

	Death	Survival	High growth	Total
Birth	57.20	40.54	2.26	100.00
	(3084)	(2186)	(122)	(5392)
Survival	36.54	60.21	3.25	100.00
	(1101)	(1814)	(98)	(3013)
High growth	34.09	57.39	8.52	100.00
	(60)	(101)	(15)	(176)
Total	49.47	47.79	2.74	100.00
	(4245)	(4101)	(235)	(8581)

Pooled Markov probabilities; frequencies in parenthesis

Source: microdata obtained from the Institut National de la Statistique.

To assess high-growth persistence in Côte d'Ivoire, we follow Hölzl (2014) and Daunfeldt and Halvarsson (2015) in computing transition probabilities into growth categories from one period to the other. The resulting stochastic matrix is reported in table 5, where lines and columns indicate current and future status, respectively.[18] The basic picture is that the probability of repeating OECD

[18] These transition matrices pool status transition in 2006 and 2009 in order to have the highest sample size possible with our data covering the 2003-2012 period. Choosing another year for observing the transition does not change the basic insight but roughly halves the sample.

high-growth status (8.52%) is much lower than that of repeating other status, e.g. 60.21% probability to stay in the market ("survive") conditional on being in the market and not experiencing high growth.[19]

However, the really striking difference with respect to the developed countries experience appears off the main diagonal. The likelihood that a HGF exits after its high-growth spell seems very high, between 25 and 40 percent. This is arguably the most significant instance where the Ivorian experience does not fit the stylized facts, as HGF in developed countries are more likely to experience moderate growth in the subsequent periods. This extreme exit rate amongst HGF is reminiscent of the high unconditional exit rate. The Markov probability of exit upon entry is almost 60 percent; another take on the same phenomenon is that the survival probability is about 50 percent. Again, this evidences a life cycle for Ivorian firms that is very different from the one that firms experience in advanced economies; in Austria, for example, the survival probability of ongoing firms is about 90 percent (Hölzl, 2014, table 4).[20]

5.6 Predictive power of firm-level characteristics

The low persistence of high-growth episodes makes targeting policies difficult to implement. Several studies confirm that predicting high growth is hard (see the review by Coad and Hölzl, 2012). Even though some factors are known to be significantly correlated with growth, such as age and size, the coefficient of determination of models of high growth is low, typically around ten percent (e.g. Coad, 2007, table 7.1).

In order to provide preliminary evidence with that respect in the case of Côte d'Ivoire, we regress a simple linear probability model on the three HGF definitions.[21] We test four different specifications, of which the results are reported in table 6. The base specification includes age, size and the interaction between age and size, and we sequentially include year, industry and firm fixed effects. When appropriate, wee also include dummy variables for high-technology and knowledge-intensive industries, as well as a dummy variable that indicates if

[19] Cross-definitions differences exist, as in developed economies; in particular, the more biased towards big firms the definition of high growth, the more persistent. However, the big picture is qualitatively similar, hence we do not report tables based on the other two definitions.

[20] Note that here we consider new firms as well, which exacerbates the difference in surviving probabilities between Hölzl's study and ours since new firms typically have a higher exit rate than ongoing ones.

[21] Our estimated dummy variable models are fully saturated, which enables us to use ordinary least squares without loss of generality regarding the distribution of the independent variable. Moreover, for each of our specifications, more than 95 percent of predicted values fall in the $[0, 1]$ interval. Finally, resorting to non-linear limited dependent variable models such as logit and probit produce qualitatively similar results.

Table 6: Linear probability model for HGF status, Côte d'Ivoire, 2003-2012.

	OECD definition			Top 5% growth			Top 5% Birch		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Age	-0.012	-0.009	0.031	-0.022**	-0.019*	0.020	-0.021**	-0.017	0.069***
	(0.015)	(0.015)	(0.050)	(0.010)	(0.010)	(0.028)	(0.010)	(0.010)	(0.027)
Base year size	0.025**	0.018	-0.315***	-0.006	-0.009	-0.199***	0.044***	0.042***	-0.083***
	(0.012)	(0.012)	(0.028)	(0.008)	(0.008)	(0.014)	(0.008)	(0.008)	(0.014)
Base size × Age	-0.026**	-0.026**	-0.023	-0.006	-0.007	-0.018*	-0.003	-0.005	-0.034***
	(0.011)	(0.011)	(0.016)	(0.008)	(0.008)	(0.011)	(0.008)	(0.008)	(0.011)
Abidjan	0.004	0.001		0.009	0.010		-0.016*	-0.013	
	(0.013)	(0.013)		(0.007)	(0.007)		(0.009)	(0.008)	
Knowledge intensive	0.010			0.018***			0.010		
	(0.011)			(0.007)			(0.007)		
High technology	0.014			0.030			0.087**		
	(0.032)			(0.023)			(0.042)		
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry fixed effects	no	yes	yes	no	yes	yes	no	yes	yes
Firm fixed effects	no	no	yes	no	no	yes	no	no	yes
R-squared	0.029	0.051	0.193	0.037	0.050	0.218	0.080	0.101	0.071
Observations	6,962	6,962	6,962	12,613	12,613	12,613	12,613	12,613	12,613

Dependent variable: latent HGF status
Size and age in logarithm
Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: microdata obtained from the Institut National de la Statistique.

the firm is located in Abidjan, given the overwhelming majority of firms located there.

Irrespective of the specification, the basic insight is that firm-level characteristics explain very little in Côte d'Ivoire. The coefficient of determination lies in the range of two to five percent, and increases significantly for the within estimator. Moreover, the estimated beta coefficients are of very low magnitude, and their sign depends on the chosen HGF definition (and on the specification). High-growth events seem as difficult to predict in Côte d'Ivoire as in advanced economies.

5.7 Implications of definition choices

It is well known that arbitrary choices with respect to growth indicators and measurement are not neutral in selecting a subset of firm population samples (see Wiklund et al., 2009). Amongst known biases, let us mention the choice between relative and absolute measurement (Schreyer, 2000) or the fact employment and sales growth are the manifestation of different phenomena (Delmar et al., 2003). These arbitrary choices have consequences in terms of policy implications, especially if different firm-level performance measures are negatively correlated (Daunfeldt et al., 2014). Moreover, different HGF definitions select different set of firms. In particular, HGF defined based on the Birch index will typically be bigger and older than those defined solely based on growth, while OECD HGF are usually found between these two extremes.

Table 7: Correlation coeficients across HGF definitions, Côte d'Ivoire, 2006-2012.

	OECD definition	**Top 5% growth**	**Top 5% Birch**
OECD definition	1		
Top 5% growth	0.529	1	
Top 5% Birch	0.502	0.386	1
Observations	12613		

Source: microdata obtained from the Institut National de la Statistique.

Definitions matter in the case of Côte d'Ivoire as well. Correlation coefficients between the different HGF definitions, which range from 40 to 50 percent, indicate that our three definitions select different firms. Table 8 reports age, size, average wage and labor productivity at the beginning of every three-year period by HGF definition and shows that differences in firm-level characteristics across definitions exhibit the already observed pattern linked to size bias. Note that we will look at the link between productivity and high growth more in detail in the next section.

Altogether, the evidence on age and size warrant more explanations. The av-

erage OECD HGF is ten-year old (median 6) and employ 119 workers (median 26). However, among other basic descriptive statistics, table 1 reports population mean and median firm age at 8.3 and 5 years, respectively, while mean and median size are 47 and 6 workers, respectively. Yet, mean differences between HGF and non-HGF reported in table 3 indicate that OECD HGF are younger and smaller than other eligible firms. This emphasized the importance of taking into account the substantial proportion of firms that exit the market before they reach the age of three, hence are not eligible for high-growth status.

Table 8: HGF characteristics across definitions, Côte d'Ivoire, 2006-2012.

	OECD def.		**Top 5% growth**		**Top 5% Birch**	
	mean	median	mean	median	mean	median
Age	10	6	4.9	3	14	9
Size	119	26	31	4	532	128
Average wage	2.9	1.9	3.6	1.7	3.1	1.7
Labor productivity	5.5	4	4.8	3.7	6.6	3.6
Observations	649		634		634	

All variables measured at the beginning of the three-year period
Average wage in million CFA per worker
Labor productivity in million CFA value added per worker

Source: microdata obtained from the Institut National de la Statistique.

6 The impact of misallocation

Based on the same data we use in this paper, previous work by Cirera et al. (2017; 2016) has shown that resources are severely misallocated in Ivorian manufacturing. In this section, we investigate the impact of this within-industry allocative inefficiency on the high-growth phenomenon. To do so, we build on the HK framework to construct counterfactual series of efficient firm-level labor allocations, which we then use to infer counterfactual (or efficient) growth paths. This enables us to compare the actual (or observed) HGF prevalence to the one that would prevail absent the distortions.

6.1 Methodology

Based on a broad consensus in the literature, we start from the premiss that developing economies are characterized by a number of distortions that create wedges between the marginal products of capital and labor across firms. As a consequence, the allocation of resources across firms is suboptimal, which results in lower aggregate productivity.

In their seminal paper, Hsieh and Klenow (2009) build a standard model of monopolistic competition where firms are heterogeneous à la Melitz (2003). Importantly, firms differ in their efficiency level *and* in the distortions they face. As a consequence, factor allocation across firms does not only depend on firm idiosyncratic productivity, but also on these distorsions. In this section, we limit ourselves to highlighting the relevant part of the HK methodology that enables us to disentangle the impact of distortions on labor allocation.

HK consider an economy that consists of S manufacturing industries. The essence of their model lies in the structure of preferences, which are assumed to be CES, and in the existence of firm-specific distortions. Industry s output in year t is given by a standard Dixit-Stiglitz aggregator of M_S differentiated products as

$$Y_{st} = \left(\sum_{i=1}^{M_S} Y_{ist}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{2}$$

where σ is the constant elasticity of substitution between varieties. Each firm i in industry s produces a differentiated variety based on a Cobb-Douglas technology that combines capital K_{ist} and labor L_{ist} inputs in constant, industry-specific proportions α_s. The associated output is given by

$$Y_{ist} = A_{ist}\, K_{ist}^{\alpha_s}\, L_{ist}^{1-\alpha_s} \tag{3}$$

where A_{ist} is the firm idiosyncratic productivity level and the crucial element for our analysis. Because there exist firm-specific distortions that affect the relative price of factors, the maximization program of the firm is

$$\pi_{ist} = (1 - \tau_{Yist})\, P_{ist}\, Y_{ist} - w_{st}\, L_{ist} - (1 + \tau_{Kist})\, R_{st}\, K_{ist} \tag{4}$$

and reflects the existence of the firm-specific output and capital wedges τ_{Yist} and τ_{Kist} that prevents the equalization of marginal products across firms.[22] Note that before-tax factor prices w_{st} and R_{st} are industry-year specific.

Profit maximization implies that output price is a constant markup over marginal cost *inclusive of the wedges*. Together with the production function, the first order condition yield firm-level conditional factor demands and capital-labor ratio. Because employment is our metrics for firm size and growth, we focus on

[22] The wedges can better be thought as taxes: after-tax marginal products are equalized across firms, but factor allocation depends on before-tax marginal products, which differ across firms since distortions are firm-specific.

labor allocation, which can be written as

$$L_{ist} = \lambda_{st} \frac{A_{ist}^{\sigma-1} \left(1 - \tau_{Yist}\right)^{\sigma}}{\left(1 + \tau_{Kist}\right)^{\alpha_s(\sigma-1)}} \tag{5}$$

where $\lambda_{st} \equiv \frac{1-\alpha_s}{w_{st}} \left[\left(\frac{1-\alpha_s}{w_{st}} \right)^{1-\alpha_s} \left(\frac{\alpha_s}{R_{st}} \right)^{\alpha_s} \frac{\sigma-1}{\sigma} P_{st} \right]^{\sigma-1} \frac{\sigma-1}{\sigma} P_{st} Y_{st}$ is an industry-year-specific demand shifter. The above expression explicitly shows how labor allocation depends on both idiosyncratic productivity and firm-specific distortions: in particular, firm-level labor input decreases in the idiosyncratic distortions they face in proportion to the economy-wide substitution elasticity and to the industry-specific capital share.

Equation (5) indicates that, in the absence of distortions, within-industry labor allocation solely depends on the idiosyncratic productivity level and on the substitution elasticity. Although physical productivity is typically not observed, the HK framework offers a very simple way to back it from revenue productivity: under the assumption of CES preferences and profits maximization, physical output is just a $\sigma/\sigma - 1$ power transformation of nominal output $P_{ist}\, Y_{ist}$. Hence we can write idiosyncratic productivity as

$$A_{ist} = \kappa_{st} \frac{\left(P_{ist}\, Y_{ist}\right)^{\frac{\sigma}{\sigma-1}}}{K_{ist}^{\alpha_s}\, L_{ist}^{1-\alpha_s}}. \tag{6}$$

where the scalar $\kappa_{st} \equiv \left(P_{st} Y_{st}\right)^{-\frac{1}{\sigma-1}} P_{st}^{-1}$ is an unobservable industry-year-specific scalar and the counterpart of the demand shifter mentioned above.

A priori, equations (7–8) are sufficient to back the efficient within-firm labor allocation from our balance sheet data. The fact that we do not observe the industry deflator P_{st} constitute our essential methodological constraint, since it implies that we cannot recover the first moments of labor allocation. Our analysis rests on two essential grounds. First, we are interested in employment *growth* rather than level, which rids ourselves of the time-invariant component of the demand shifter. Second, the efficiency concept we rely on is a within-industry one. This is consistent with the literature on resource misallocation and, more broadly, with the entire monopolistic competition framework which typically does not model between-industry interactions. Therefore, we demean growth at the industry-level in order to compare the growth path of firms in different industries, and the industry-invariant part of the demand shifter cancels out as a consequence.[23]

We build our measure of counterfactual firm growth as follows. In the absence

[23] Note however that the typical HGF analysis is performed at the aggregate level, although there are a few exceptions, particularly when looking at persistence. See e.g. Daunfeldt and Halvarsson (2015) and Moschella et al. (2017).

of distortions, labor allocation only depends on firm idiosyncratic productivity and the industry-year demand shifter. From (5) and (6), the optimal (log) labor allocation is

$$\log \overset{o}{L}_{ist} = (\sigma - 1) \log \kappa_{st} + \sigma \log \frac{P_{ist}\, Y_{ist}}{K_{ist}^{\alpha_s}\, L_{ist}^{1-\alpha_s}}, \tag{7}$$

which we cannot directly compute from the data because of the scalar κ_{st}. Therefore we demean the series at the industry-year level as

$$\log \tilde{L}_{ist} = \sigma \log \frac{P_{ist}\, Y_{ist}}{K_{ist}^{\alpha_s}\, L_{ist}^{1-\alpha_s}} - \frac{\sigma}{M_S} \sum_{i=1}^{M_S} \log \frac{P_{ist}\, Y_{ist}}{K_{ist}^{\alpha_s}\, L_{ist}^{1-\alpha_s}} \tag{8}$$

where the demand shifter cancels out. We then take first differences to obtain our measure of optimal growth path

$$\dot{L}_{is}(t) = \log \tilde{L}_{is}(t) - \log \tilde{L}_{is}(t-1) \tag{9}$$

which we can use and compare across industries.

Finally, we parametrize the model following Cirera et al. (2016). We use labor compensation rather than employment level to account for heterogeneity in human capital and hours worked across firms. Because the extent of reallocation increases with the substitution elasticity, we conservatively set the latter to three.[24] Regarding factor shares, we assume the same factor intensities as in the U.S., which serve as undistorted benchmark. We set the capital share to one minus the labor share in the corresponding industry in the NBER Productivity Database. We take averages over 2003-2012, so that our industry-specific shares are constant across time and our decomposition exercise is not polluted by industry-specific technical change. Moreover, we follow previous works and inflate the labor cost by 50 percent to account for fringe benefits and social security contribution in the U.S. Note that we do not need to assume anything about the rate of return to capital as far as our analysis is concerned.

6.2 Methodological constraints

We perform our misallocation analysis based the method described above to construct counterfactual growth. In line with the literature, the exercise is limited to the manufacturing sector. As stressed in the data section, it is fairly demanding in terms of balance-sheet information, hence the sample on which we perform the analysis is much reduced compared to the stylized facts investigated earlier (see HK sample in table 1).

[24] In reality, the elasticity vary across varieties and industries; we acknowledge this limitation of our analysis, which is inherent to quantitative research based on CES preferences.

Moreover, as equation 5 indicates, we cannot back the efficient labor allocation from the data without problematic assumptions on the rate of return. [25] Hence we rely on industry-year demeaned growth rates, which raises issues with respect to the OECD and the Birch definitions. Because the latter combines absolute and relative changes, it cannot straightforwardly accommodate demeaning, and we will not use it for the misallocation analysis. Yet, we do not want to renounce to using the OECD definition altogether, because its characteristic 20% annual growth threshold enables us to assess the increased prevalence of HGF in a way that a quantile-based definition does not. Therefore, we stick to our main definition but demean the growth threshold at the industry-year level and get rid of the size threshold of ten employee. In practice, more than 85 percent of firms in our HK sample employ at least ten workers. Moreover, the sample only contains 16 firms (corresponding to 22 firm-year observations) that grow at a faster than 20 percent annually for three years with a base size of fewer than ten workers, and 11 of them (15 firm-years) end up employing more than ten workers.

6.3 Observed v. efficient growth rates

Figure 3 shows the density of growth rates pre- and post-reallocation. The first thing to note is that the efficient reallocation of resources widens the distribution of growth rates by construction, implying a higher density of extreme growth events. Therefore, there will be more HGF in the counterfactual economy by our definition, since more firms reach the growth threshold.

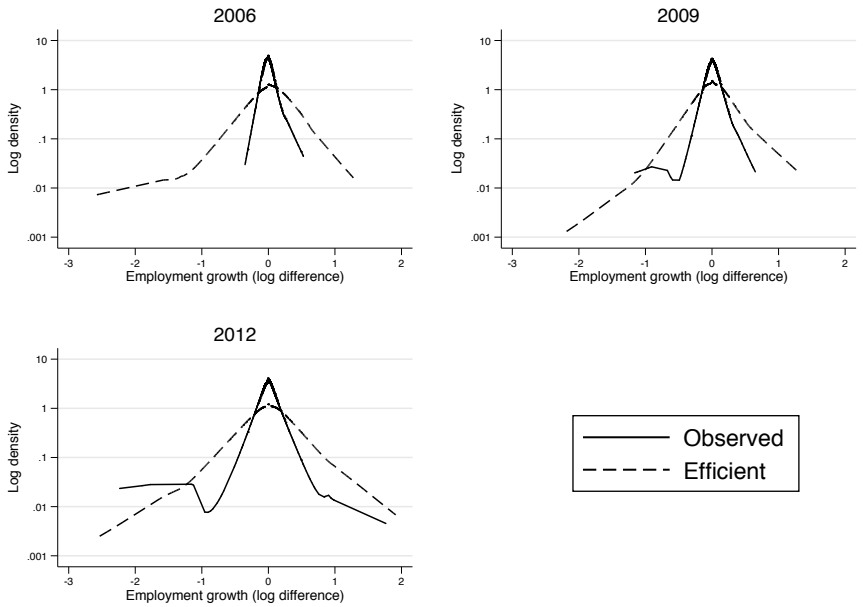
Table 9 reports the yearly count of counterfactual HGF compared to actual ones. Each year, between 34 and 51 firms are counterfactual HGF, which corresponds to a more than twofold expansion on average. However, the selected firms are not the same (Pearson's correlation coefficient between the two latent variables is even negative). In order to emphasize the impact of misallocation, our preferred approach consists in characterizing firms status jointly in the actual and the counterfactual economy. The main insight from table 10 is that less than one fifth of actual HGF would also have that status were resource allocated efficiently; moreover, one quarter of the firms that do not grow fast by our definition would do so in a distortion-free economy.

6.4 Size, age and the life cycle

Table 11 indicates that counterfactual HGF are larger older and more productive than actual ones. It is consistent with a positive correlation between productivity (of which size is a proxy) and distortions. It also suggests that distortions

[25] Equivalently, we cannot back TFPQ in the absence of industry deflators (see equation 6).

Figure 3: Observed and efficient distribution of growth rates, Côte d'Ivoire, 2006, 2009 and 2012.



Source: microdata obtained from the Institut National de la Statistique.

Table 9: Actual v. counterfactual HGF prevalence, Côte d'Ivoire, 2006-2012.

	HK sample			
	Pop.	Elig.	Actual HGF	Counterfactual HGF
2006	268	173	13	34
	(1.0000)	(.6455)	(.0751)	(.1965)
2007	281	173	16	37
	(1.0000)	(.6157)	(.0925)	(.2139)
2008	276	178	23	51
	(1.0000)	(.6449)	(.1292)	(.2865)
2009	310	179	25	47
	(1.0000)	(.5774)	(.1397)	(.2626)
2010	333	167	16	33
	(1.0000)	(.5015)	(.0958)	(.1976)
2011	388	169	17	36
	(1.0000)	(.4356)	(.1006)	(.2130)
2012	447	181	21	49
	(1.0000)	(.4049)	(.1160)	(.2707)
Total	2,303	1,220	131	287
	(1.0000)	(.5297)	(.1074)	(.2352)

Firm count; relevant share in parentheses
Share of eligible firms in the population; share of HGF in the eligible subset

Source: microdata obtained from the Institut National de la Statistique.

Table 10: Joint actual and countrefactual HGF status, Côte d'Ivoire, 2006-2012.

	Counterfactual non-HGF	Counterfactual HGF	Total
Actual non-HGF	824	265	1089
	(75.67)	(24.33)	(100.00)
Actual HGF	109	22	131
	(83.21)	(16.79)	(100.00)
Total	933	287	1220
	(76.48)	(23.52)	(100.00)

Frequencies by high-growth status; row percentage in parenthesis

Source: microdata obtained from the Institut National de la Statistique.

increase with age. Tables 12, and 14 report a similar joint actual-counterfactual status by size, age and productivity, respectively. In particular, 13 shows that the prevalence of counterfactual HGF increases wit age, which suggests that distortions get worse over the life cycle.

Table 11: Actual and counterfactual HGF characteristics, Côte d'Ivoire, 2006-2012.

	Actual HGF		**Counterfactual HGF**	
	mean	median	mean	median
Age	9	5	20	17
Size	88	28	200	70
TFPQ	43	22	235	39
Observations	131		287	

All variables measured at the beginning of the three-year period

Source: microdata obtained from the Institut National de la Statistique.

Table 12: Joint actual and counterfactual HGF status by size quartile, Côte d'Ivoire, 2006-2012.

	Counterf. non-HGF	Counterfactual HGF	**Total**
Size Q1			
Actual non-HGF	99	35	134
	(73.88)	(26.12)	(100.00)
Actual HGF	11	2	13
	(84.62)	(15.38)	(100.00)
Size Q2			
Actual non-HGF	178	65	243
	(73.25)	(26.75)	(100.00)
Actual HGF	24	4	28
	(85.71)	(14.29)	(100.00)
Size Q3			
Actual non-HGF	230	82	312
	(73.72)	(26.28)	(100.00)
Actual HGF	29	7	36
	(80.56)	(19.44)	(100.00)
Size Q4			
Actual non-HGF	317	83	400
	(79.25)	(20.75)	(100.00)
Actual HGF	45	9	54
	(83.33)	(16.67)	(100.00)

Frequencies by high-growth status; row percentage in parentheses
Size measured at the beginning of the three-year period

Source: microdata obtained from the Institut National de la Statistique.

Table 13: Joint actual and counterfactual HGF status by age category, Côte d'Ivoire, 2006-2012.

	Counterf. non-HGF	Counterfactual HGF	**Total**
Age: < 5 years			
Actual non-HGF	33	8	41
	(80.49)	(19.51)	(100.00)
Actual HGF	25	4	29
	(86.21)	(13.79)	(100.00)
Age: 5 to 10 years			
Actual non-HGF	107	30	137
	(78.10)	(21.90)	(100.00)
Actual HGF	33	6	39
	(84.62)	(15.38)	(100.00)
Age: > 10 years			
Actual non-HGF	684	227	911
	(75.08)	(24.92)	(100.00)
Actual HGF	51	12	63
	(80.95)	(19.05)	(100.00)

Frequencies by high-growth status; row percentage in parentheses
Age at the beginning of the three-year period

Source: microdata obtained from the Institut National de la Statistique.

Table 14: Joint actual and counterfactual HGF status by productivity quartile, Côte d'Ivoire, 2006-2012.

	Counterf. non-HGF	Counterfactual HGF	**Total**
TFPQ Q1			
Actual non-HGF	54	82	136
	(39.71)	(60.29)	(100.00)
Actual HGF	9	9	18
	(50.00)	(50.00)	(100.00)
TFPQ Q2			
Actual non-HGF	175	68	243
	(72.02)	(27.98)	(100.00)
Actual HGF	38	6	44
	(86.36)	(13.64)	(100.00)
TFPQ Q3			
Actual non-HGF	270	58	328
	(82.32)	(17.68)	(100.00)
Actual HGF	31	3	34
	(91.18)	(8.82)	(100.00)
TFPQ Q4			
Actual non-HGF	325	57	382
	(85.08)	(14.92)	(100.00)
Actual HGF	31	4	35
	(88.57)	(11.43)	(100.00)

Frequencies by high-growth status; row percentage in parentheses
TFPQ measured at the beginning of the three-year period

Source: microdata obtained from the Institut National de la Statistique.

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