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Markus Poschke

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Markus Poschke
McGill University,
CIREQ and IZA

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IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

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ABSTRACT

Skill-Biased Change in Entrepreneurial Technology*

In contrast to the very large literature on skill-biased technical change among workers, there is hardly any work on the importance of skills for the entrepreneurs who employ those workers, and in particular on their evolution over time. This paper proposes a simple theory of skill-biased change in entrepreneurial technology that fits with cross-country, historical and micro evidence. For this, it introduces two additional features into an otherwise standard occupational choice, heterogeneous firm model à la Lucas (1978): technological change does not benefit all potential entrepreneurs equally, and there is a positive relationship between an individual's potential payoffs in working and in entrepreneurship. If some firms consistently benefit more from technological progress than others, they stay closer to the frontier, and the others fall behind. Because wages rise for all workers, low-productivity entrepreneurs will then at some point exit and become workers. As a consequence, the entrepreneurship rate falls with income per capita, average firm size and firm size dispersion increase with income per capita, and "entrepreneurship out of necessity" falls with income per capita. The paper also documents, for two of the facts for the first time, that these are exactly the relationships prevailing in cross-country data. Quantitatively, the model fits the U.S. experience well. Using the parameters from a calibration to the U.S., the model also explains cross-country patterns quite well.

JEL Classification: E24, J24, L11, L26, O30

Keywords: occupational choice, entrepreneurship, firm size, firm entry, growth, skill-biased technical change

Corresponding author:

Markus Poschke
McGill University
Economics Department
855 Sherbrooke St West
Montreal QC H3A 2T7
Canada
E-mail: markus.poschke@mcgill.ca

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1 Introduction

In contrast to the very large literature on skill-biased technical change among workers, there is hardly any work on the importance of skills for the entrepreneurs who employ those workers, and in particular on their evolution over time. This paper proposes a simple theory of skill-biased change in entrepreneurial technology that fits with cross-country, historical and micro evidence.

Technological change is taken for granted as the main historical driver of growth in developed economies. While different types of technological change apart from the neutral variety have received a lot of attention in the recent literature (see e.g. Greenwood, Hercowitz and Krusell (1997) on investment-specific technological change, Krusell, Ohanian, Rios-Rull and Violante (2000) on capital-skill complementarity, Katz and Murphy (1992) on skill-biased technical change and the demand for workers or Hornstein, Krusell and Violante (2005) on links among the three), there has been barely any work on how technological change affects entrepreneurs. Yet, entrepreneurs need to implement the technologies that they and their employees then operate, so the effect of technical change on entrepreneurs is of crucial importance for how technology subsequently affects labor demand, wages and employment. This paper aims to fill that gap by proposing and taking seriously a very simple theory of technology and entrepreneurship.

If changes in technology affect incentives to become an entrepreneur, the evolution of technology helps shape the firm size distribution. Section 2 presents evidence that this is indeed the case. It uses historical U.S. data and data from the Global Entrepreneurship Monitor, a survey conducted in around 50 countries that focusses on obtaining internationally comparable information on entrepreneurs. To the best of my knowledge, this is the first paper using information from that survey for macroeconomic analysis. The section establishes four facts. First, the entrepreneurship rate falls with per capita income across countries. Second, average firm size increases with per capita income. The first fact fits with the finding of Gollin (2007) that the self-employment rate falls with per capita income in ILO cross-country data. The second one extends Lucas's (1978) results to more recent U.S. data and into the cross-country dimension. The next two facts are new: Third, the standard deviation of firm size increases with per capita income both across countries and in U.S. history. Fourth, the fraction of entrepreneurs claiming to have chosen their occupation "out of necessity and not to pursue an opportunity" falls with per capita income across countries. Lucas (1978) and Gollin (2007) provide explanations for the first two facts, but their models do not fit the other two facts.

The data thus show a relationship between the level of development and features of the firm size distribution. The paper shows that this can be explained in an otherwise standard occupational choice model à la Lucas (1978) with two additional features: technological change not benefitting all potential entrepreneurs equally, and a positive relationship between an individual's potential payoffs in working and in entrepreneurship.

Anyone who has programmed a VCR or tried to set up a home computing network will appreciate that while technological progress brings productivity advances, it often goes along with increased complexity of technology. This is even more so for firms, and not just for large or "high-tech" ones. Consider the corner shop owner contemplating the installation of bar code scanners. This allows automating inventory control, but requires managing the related computing infrastructure. Or consider the owner of a car repair shop who needs to master the increasing amount of computing power of customers' cars. This allows for faster diagnostic checks, but also requires mastering technology that is quite distinct from the core technologies used in that business.

As the menu of available technologies expands, raising aggregate productivity (assuming love of variety, as in Romer 1987), individual firms have to cope with increasing complexity of technology. To reflect this, the key assumption in the model, which otherwise is a standard occupational choice model à la Lucas (1978), is that, while advances in the technological frontier raise all firms' productivity, they do not affect all firms equally. Some firms absorb more of a given technology improvement than others, or are more able to use a new technological opportunity. As a result, some firms remain close to the frontier and use a production process involving many, highly specialized inputs, while others fall behind the frontier, use a simpler production process, and fall behind in terms of relative productivity.[1]

The second crucial assumption is that agents differ in their labor market opportunities and that more productive workers can also manage more complex technologies if they become entrepreneurs. Occupational choice between employment and entrepreneurship closes the model. Because advances in the technological frontier do not benefit every potential entrepreneur equally, the position of the frontier then governs occupational choice. The more advanced the frontier, the greater the benefit from being able to stay close to it, as other firms fall behind. Because in equilibrium, advances in the frontier also raise wages, entrepreneurs' outside option

[1]Jovanovic and Rousseau (2008) document that from 1971 to 2006, the average yearly growth rates of the stocks of patents and trademarks in the U.S. were 1.9% and 3.9%, respectively, implying a substantial increase in variety. Similarly, every new classification of occupations in the U.S. from 1970 to 2010 lists more occupations than the preceding one (Scopp 2003). At the same time, Cummins and Violante (2002) find that the gap between the frontier and average technology in use has been increasing in the U.S. over the entire span of their data (1947-2000), implying that firms have not all benefitted equally from technology improvements.

improves, and marginal entrepreneurs exit. The result is a "history", explored in Section 4, in which high-productivity entrepreneurs are gradually drawn into the market as their productivity improves more than others'. Their entry raises labor demand and the wage, implying that low-productivity entrepreneurs eventually find employment more attractive and exit.[2]

The need for skills to deal with a broad array of technologies at the same time is in line with Lazear's (2004, 2005) finding that entrepreneurs tend to have more general skills than employees. It also fits with evidence from the burgeoning recent literature on CEOs and CEO pay, which shows that the importance of general skills has risen of late (see e.g. Murphy and Zabojnik 2004, Rajan and Wulf 2006, Frydman 2007).[3] These skills are usually measured as the variety of someone's experience of different industries, companies, functions within companies (e.g. production, marketing, finance), and thus technologies. The main reasons for this phenomenon suggested by that literature are a growing need to master more technologies at the same time and broader responsibilities that come from flatter hierarchies made possible by advancing information technology. If entrepreneurs want to benefit from the new possibilities put on the menu by technological advances, they need to keep up with technological developments. The degree to which they can do so determines how many benefits they reap from technological progress.[4]

While the effects of this development on organizational hierarchies and CEO pay have received a lot of attention recently,[5] the general equilibrium implications have not been studied. Yet, they are substantial, as incentives for entrepreneurship determine not just individual occupational choice and entrepreneurs' incomes, but also the firm size distribution, aggregate labor demand, the level of aggregate technology that is actually in place, and output. Analyzing this

[2]As there is an across-the-board productivity increase in the model as the frontier advances, it also allows for certain tasks that used to be at the technological frontier to be achieved by entrepreneurs behind the frontier as technological advances. Think e.g. about multimedia; a professional can now do on a single computer what in earlier times would have required much more resources. Yet, the frontier moves on – the professional benefits, but entrepreneurs closer to the frontier now can use even more advanced technology.

[3]Of course, CEOs and entrepreneurs do not fulfill exactly the same functions. Still, their job content is rather similar, with the main difference being the importance of the willingness to take risk. As this will not play a prominent role in this paper, CEOs are an informative group of comparison.

[4]This is qualitatively different from the need for employees to keep up with technology: employees need to apply a given technology, while entrepreneurs need to choose and coordinate the technologies used in a firm's production process. So even if technological progress had de-skilling elements in the 19th century, as argued by James and Skinner (1985) and by Cain and Paterson (1986), replacing skilled workers with machinery still made increasing demands on entrepreneurs to understand and coordinate the new technologies that now were available in addition to the old ones. The setting here thus does not depend on complementarity between capital and workers' skills; all that is needed is that keeping up with advancing technology is costly for entrepreneurs.

[5]Important references include Garicano (2000), Gabaix and Landier (2008) and Terviö (2008). For a survey of the CEO literature see Bertrand (2009).

is the main contribution of this paper. While the assumptions made here on the use of technology are admittedly much simpler than those in the micro literature, they make it possible to transparently obtain a full set of general equilibrium results and compare these to the evidence.

The calibration exercise in Section 5 shows that the model fits the U.S. experience, including the history of average firm size, well. Although not targeted in the calibration, it also generates a trend in income concentration at the top very similar to that documented by Piketty and Saez (2006). More strikingly, using parameter values from the calibration to the U.S., the model matches not only the qualitative relationship between per capita income and the entrepreneurship rate, average firm size, firm size dispersion and the share of necessity entrepreneurs across countries, but actually delivers a good quantitative fit for some of these dimensions. In particular, the predicted changes in the entrepreneurship rate and in average firm size with per capita income are very close to those in the data. Because of its stylized nature, the model overpredicts the sensitivity of firm size dispersion and the share of necessity entrepreneurs to per capita income.

Skill-biased change in entrepreneurial technology thus is a convenient way of taking results from the micro literature on entrepreneurs and skills to macroeconomics. In addition, the concrete model proposed here fits the U.S. experience well and helps to explain cross-country differences in entrepreneurial choice and in the firm size distribution across countries.

Besides the references above, this paper is related to two further strands of literature. First, several papers have analyzed entrepreneurial choice. Cagetti and De Nardi (2006) fit a model of entrepreneurial choice to U.S. data with the aim of assessing the contribution of entrepreneurship and credit constraints to wealth inequality. Their model does not involve changes in entrepreneurial choice with development. Entrepreneurial choice and development has been analyzed by Banerjee and Newman (1993) and Lloyd-Ellis and Bernhardt (2000). These papers also focus on the role of the wealth distribution when there are credit constraints, but do not feature an evolving role for skills as the present paper does.

Secondly, some papers have taken a similar view of skills, complexity or the role of the entrepreneur as this paper. Teulings (1995) relates skills to the ability to deal with complexity, but does not consider entrepreneurship. Lloyd-Ellis (1999) assumes that skill is required for implementing a technology, but focusses on the tradeoff between using skills for R&D or for implementation. Jovanovic and Rousseau (2008) also model a manager's task as finding the right combination of heterogeneous inputs but focus on the quality of the match between a firm's products and its workers' skills, not on the evolution of entrepreneurial choice and the firm size distribution with development.

The paper is organized as follows. Section 2 describes the GEM dataset and documents relevant facts about entrepreneurship and the firm size distribution. Section 3 presents the model, and Section 4 shows how entrepreneurship and characteristics of the firm size distribution change with development. Finally, Section 5 presents a generalization of the model and quantitative results, and Section 6 concludes.

2 Entrepreneurship, the firm size distribution and development

Obtaining data on the firm size distribution across countries is notoriously hard because measurement is not harmonized across countries. The relatively new Global Entrepreneurship Monitor (GEM) dataset is an exception.[6] To the best of my knowledge, this is the first paper using GEM data across countries for macroeconomic analysis. As this is a new dataset and probably is not well known to macroeconomists, I briefly present it in the next subsection.

The remainder of the section then shows four facts on occupational choice and the firm size distribution across countries obtained using the GEM data: entrepreneurship and the self-employment rate fall with per capita income, average firm size increases with per capita income, the standard deviation of firm size increases with per capita income, and the fraction of entrepreneurs claiming to have chosen their occupation "out of necessity and not to pursue an opportunity" falls with per capita income. The first two facts are known yet worth revisiting, while the last two are new.

2.1 The Global Entrepreneurship Monitor (GEM) survey

The GEM is an individual-level survey run by London Business School and Babson College now conducted in more than 50 countries. Country coverage has been expanding since its inception in 1999, with data for several years available for most countries. The micro data is in the public domain, downloadable at `http://www.gemconsortium.org/`. Most developed economies are represented, plus a substantial number of transition and developing economies, ensuring that the data covers a wide variety of income levels.[7]

[6] Another exception are some OECD publications such as Bartelsman, Haltiwanger and Scarpetta (2004) that provide information on some OECD countries and a limited number of other countries. Their numbers arise from an effort to harmonize national official data, while the GEM approach already involves harmonized data collection (though inevitably at a smaller scale).

[7] Inclusion in the survey depends on an organization within a country expressing interesting and financing data collection.

The survey focusses on entrepreneurship. That is, while the survey overall is conducted by local research organizations or market research firms to be representative of a country's population, it contains only limited demographic information (e.g. education) on non-entrepreneurs. It contains much richer information on entrepreneurs, including on firms in the start-up phase (a particular focus of the survey). In particular, entrepreneurs report their firm's employment.

Importantly, the survey is designed to obtain harmonized data across countries. It is thus built to allow cross-country comparisons, the purpose for which it is used here. In addition, because it is an individual-level survey, it captures all types of firms and not just firms in the formal sector or above some size threshold. For studying occupational choice, this is evidently important. This feature makes the GEM data more adequate for the purposes of the analysis in this paper than firm- or establishment-level surveys such as the World Bank Group Entrepreneurship Survey, which covers only registered corporations, or Dun & Bradstreet data, which is reasonably representative of U.S. firms but does not cover many small firms in other countries, especially in poorer ones.

To obtain data on entrepreneurship rates and necessity entrepreneurship, I use country averages of the country-level data covering the years 2002-2008 available on the GEM website for 66 countries. Micro data is available for 1999 to 2005 and covers fewer countries. I use it to obtain statistics on the firm size distribution, for which no country-level numbers are reported. As the initial years of the survey may be less reliable, I use the micro data for the period 2001-2005. For this period, data is available for 47 countries, though not for all years for all countries. Pooling the available years for each country, the number of observations per country is between 2,000 in some developing economies and almost 80,000 in the UK, with a cross-country average of 11,700. This is sufficient for computing the summary statistics of the firm size distribution that I use in the following. Unfortunately, in many countries, there are not enough observations for obtaining reliable estimates for detailed size classes, so I rely on summary statistics for the entire distribution. I consider someone an entrepreneur if they declare running a firm that they own and they have already paid wages (possibly to themselves, for the self-employed). I then obtain firm size data for these firms, truncating the distribution at 1000 employees to reduce measurement error.

The GEM dataset is very useful because of the harmonized data collection. Moreover, it allows establishing all facts of interest using one single dataset. However, it is still important to know that results hold more generally, and are not due to specificities of the survey. Therefore, I compare the facts presented here to some results from other sources. In addition, Reynolds et al.

(2005), Acs, Desai and Klapper (2008) and Ardagna and Lusardi (2008) show that observations from GEM data tend to align well with those based on other sources.

2.2 The facts

Figure 1 plots statistics on entrepreneurship and the firm size distribution against 2005 real GDP per capita at purchasing power parity from the Penn World Tables (Summers and Heston 1991, Heston, Summers and Aten 2009).[8] Each subfigure illustrates one of the following four facts:[9]

Fact 1 *The entrepreneurship rate falls with income per capita (see Figure 1(a)).*

This fits with the finding of Gollin (2007) that the self-employment rate falls with income per capita in ILO data. Although the negative relationship between the entrepreneurship rate and per capita income is very robust, it does not seem to be well known. A possible reason for that is that the population of entrepreneurs under consideration matters. The fact holds for broad measures of entrepreneurship that include small firms and, in particular, the self-employed. When considering only incorporated firms, the relationship is reversed. This is the case for instance in data from the World Bank Group Entrepreneurship Survey, which covers only registered corporations. This positive relationship is often attributed to differences in regulation; see e.g. Klapper, Laeven and Rajan (2006) and Barseghyan (2008). For studying occupational choice, focussing on registered firms is not sufficient and it is necessary to take into account all firms, as in the GEM or ILO data.[10]

Fact 2 *Average firm employment increases with income per capita (see Figure 1(b)).*

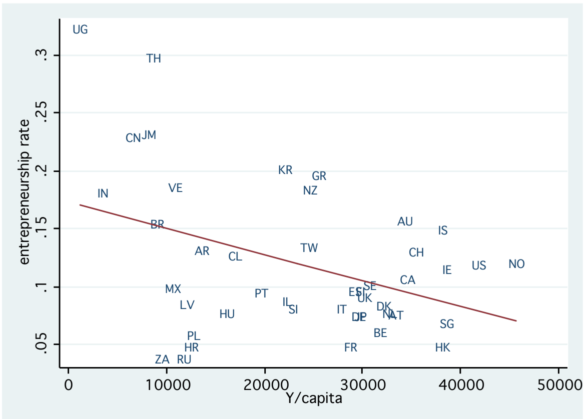
This fact is of course closely related to fact 1, as high entrepreneurship rates must necessarily imply smaller average employment.[11] Previously, this relationship has only been documented across a limited number of countries (Tybout 2000). In addition, Lucas (1978) reported that

[8] By its sampling procedure, the survey captures few agricultural businesses (only 4% on average). As self-employment is typically higher and income per capita typically lower in agriculture (see e.g. Caselli 2005, Restuccia, Yang and Zhu 2008), the facts presented in the following would be even more pronounced if they could be produced using a reliable up-to-date measure of non-agricultural GDP per capita at PPP.

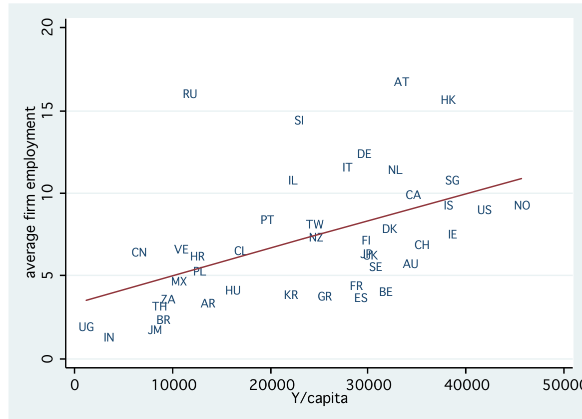
[9] All regression lines plotted in the figure are significant at least at the 5% level.

[10] In U.S. history, the self-employment rate fell continuously until the mid-1970s, when it temporarily rebounded for a few years, mainly due to changes in tax rates (Blau 1987; see also Hipple 2004).

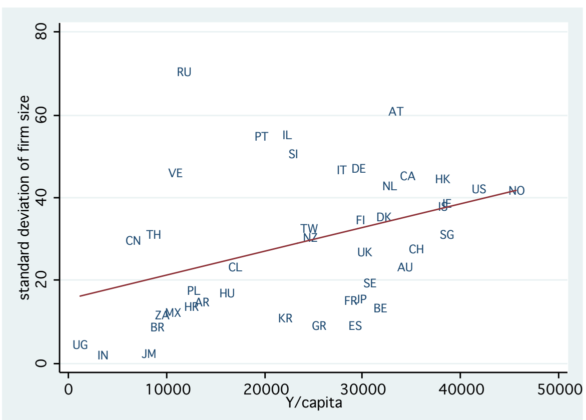
[11] Strangely enough, this simple relationship often seems to escape policy discussions on promoting entrepreneurship.



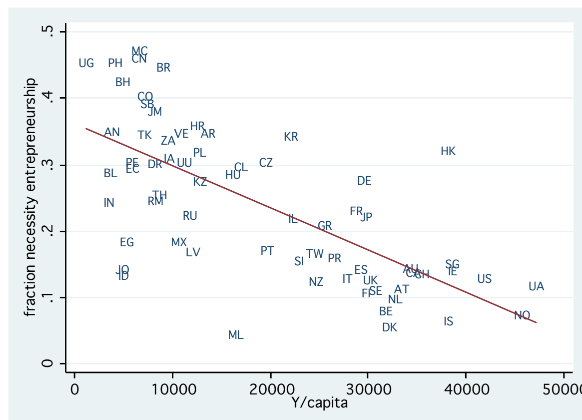
(a) The entrepreneurship rate



(b) Average employment



(c) The standard deviation of employment



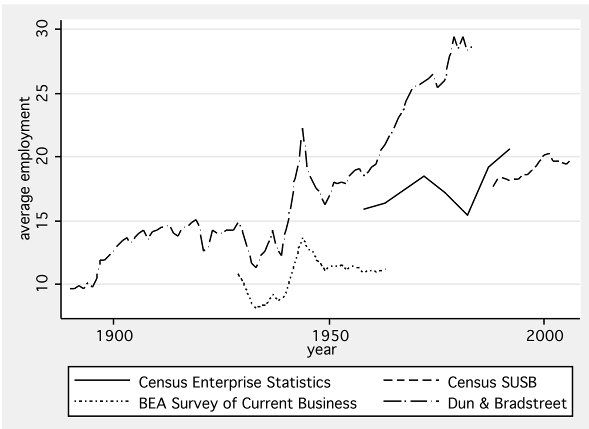
(d) The share of necessity entrepreneurs

Figure 1: Entrepreneurship, the firm size distribution and per capita income.

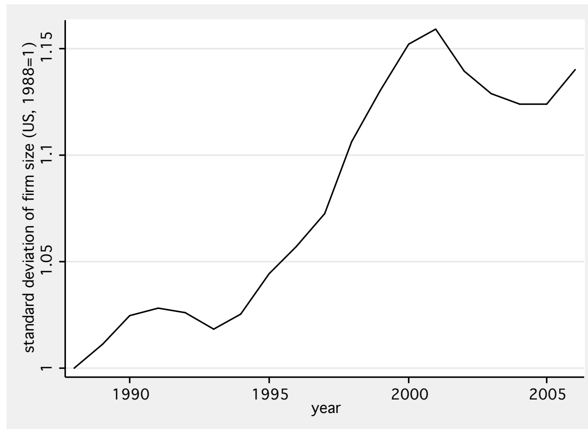
Notes: Real GPD per capita for 2005 at purchasing power parity from the Penn World Tables (Summers and Heston 1991, Heston et al. 2009); entrepreneurship rate, average employment, standard deviation of employment and share of necessity entrepreneurs from GEM data, `http://www.gemconsortium.org`. Entrepreneurs are defined as survey respondents who declare running a firm that they own and who have already paid wages, possibly to themselves. Necessity entrepreneurs choose the second answer when asked "Are you involved in this start-up/firm to take advantage of a business opportunity or because you have no better choices for work?" Average firm size for Latvia is 60% above the next-highest value. This may indicate data problems; the observation is therefore excluded. All regression lines plotted in the figure are significant at least at the 5% level.

average firm size increased with per capita income over U.S. history (1900-70). Figure 2(a) shows that this time-series relationship persists. It reports measures of average firm size close to those used by Lucas (the two series labelled "BEA Survey of Current Business" and "Dun & Bradstreet", both from Carter, Gartner, Haines, Olmstead, Sutch and Wright 2006) and more recent data. All of these series show an increasing trend, except for the period 1900-1930.

This trend of course occurs simultaneously with increasing per capita income. Firm size thus increases with per capita income both in U.S. history and across countries.[12]



(a) Average firm size, 1890-2006



(b) Standard deviation of firm size, 1988-2006

Figure 2: Average firm size (employment) and the standard deviation of firm size over U.S. history

Sources: Panel (a): Census Enterprise Statistics series: from various Census reports; Census Statistics of U.S. Businesses (SUSB) series: data available at `http://www.census.gov/econ/susb/`; BEA Survey of Current Business series: from Carter et al. (2006, Series Ch265); Dun & Bradstreet series: from Carter et al. (2006, Series Ch408). The first two sources also report total employment. For the last two series, employment is from Carter et al. (2006, Series Ba471-473 and Ba477). The Dun & Bradstreet firm counts exclude finance, railroads and amusements. Adjusting employment for this using Series Ba662, Dh31, Dh35, Dh53 and Df 1002 shortens the series without affecting the trend. Starting 1984, Dun & Bradstreet gradually cover additional sectors, at the cost of comparability over time, so I only use data up to 1983. Series Ch1 in Carter et al. (2006), which draws on Internal Revenue Service data, also contains firm counts but is less useful because of frequent changes of definition, in particular for proprietorships. Panel (b): Computed from Census SUSB data using reported size bin averages.

Fact 3 *The dispersion of firm size in terms of employment increases with income per capita (see Figure 1(c)).*

This is the fact for which the GEM data contribute most, as it seems impossible to obtain from other sources in a consistent way for more than a small number of countries. The figure shows a clear positive relationship between the standard deviation of firm size and per capita

[12] Jovanovic and Rousseau (2008) show that another measure of size, patents or trademarks per firm, has also increased from 1971 to 2006. For other countries, it is not easy to come by histories of average firm size. However, data reported in a special issue of *Small Business Economics* reveal that average firm size also increased with development in several East Asian economies. This is the case in Indonesia (Berry, Rodriguez and Sandee 2002), Japan (Urata and Kawai 2002), South Korea (Nugent and Yhee 2002) and Thailand (Wiboonchutikula 2002). Only in Taiwan, the smallest of these countries, did it fall (Aw 2002).

income. The only previous mention of such a relationship I could find is Bartelsman et al. (2004), who show that firm size dispersion is substantially higher in industrialized countries compared to emerging markets, using OECD and World Bank data for a much smaller set of countries. Interestingly, the relationship also holds in recent U.S. history. SBA data include the number of firms in different size classes since the 1980s and thereby allow computing an approximate measure of the standard deviation of firm size. This is plotted in Figure 2(b) and also exhibits a clear upward trend over time. Unfortunately, I am not aware of data that would allow extending this series further into the past.[13]

Finally, it is interesting to consider information the GEM data provides on entrepreneurs' motivations. The survey identifies "opportunity" and "necessity" entrepreneurs. This classification is based on the answer to the question: "Are you involved in this start-up/firm to take advantage of a business opportunity or because you have no better choices for work?" While strictly speaking this question is ill-defined – after all, choosing entrepreneurship implies that it must have been the best choice – it arguably still conveys information on how strongly the respondent identifies with the term "opportunity". Indeed, upon closer inspection, the answer to the question turns out to be significantly related to a firm's current size and growth expectations: necessity entrepreneurs have less education, run smaller firms and expect much less growth (see Ardagna and Lusardi 2008, Poschke 2010*a*). These patterns are consistent across countries. It can thus be taken to be informative about a firm's current state, and also reveals that founders can, to some degree, anticipate how successful their venture will be. This leads us to the final fact:

Fact 4 *The share of "necessity entrepreneurs" falls with income per capita (see Figure 1(d)).*

While there are necessity entrepreneurs in all economies, including in rich ones, their proportion among entrepreneurs is much higher the poorer the country. In countries with low per capita income there are thus more entrepreneurs, but a larger fraction of them chooses entrepreneurship "out of necessity". The share of "opportunity" entrepreneurs is thus smaller.

[13] Hsieh and Klenow (2009) compute TFP dispersion in China, India and the U.S.. Apart from the fact that their numbers are hard to compare to the ones obtained here because they are restricted to manufacturing and refer to establishments, not firms, they are also effectively forced to impose a size cutoff because some variables are missing for small establishments in their otherwise very rich data. This affects measured dispersion. Comparing their Table I to Census SUSB data shows that in the case of the U.S. in 2001 for instance, they need to exclude almost half the manufacturing establishments. The size distribution plotted in their Figure IX shows that these are mostly small establishments belonging to firms with less than 10 employees. While these issues are less important for the purpose of their paper, it is preferable to have firm data without a size cutoff and without the limitation to a single sector for analyzing occupational choice between wage work and entrepreneurship.

Lucas (1978) in his seminal occupational choice framework explains Fact 2 by allowing for complementarity in production between the capital and labor inputs. More productive economies accumulate more capital, which with the complementarity raises wages more than profits, reducing the share of entrepreneurs and thus raising the average size of firms. Gollin (2007) explicitly introduces self-employment as an option and then uses a similar framework to fit self-employment rates across countries (Fact 1).

In each of these cases, the agents who choose entrepreneurship are the fraction of the population that is best at it. Increases in productivity raise the threshold and reduce that fraction. While this implies that in richer countries, there are fewer and larger firms, this mechanism does not explain Facts 3 and 4. To the contrary, a more homogeneous population of entrepreneurs may well reduce the standard deviation of firm size, and the fact that it is always the more able individuals who choose entrepreneurship does not allow dealing satisfactorily with entrepreneurship out of necessity. The model developed in the next section addresses these points and thus is able to explain all four facts.

3 A simple model

The economy consists of a unit continuum of agents and an endogenous measure of firms. Agents differ in their endowment of effective units of labor $a \in [0, \bar{a}]$ that they can rent to firms in a competitive labor market. Refer to this endowment as "ability". Differences in ability can be thought of as skill differences. They are observable, and the distribution of ability in the population can be described by a *pdf* $\phi(a)$.

Agents value consumption c of a homogeneous good, which is also used as the numéraire. They choose between work and entrepreneurship to maximize consumption.[14] The outcome of this choice endogenously determines the measures of workers and of firms in the economy.

Consumption maximization implies that individuals who choose to be workers supply their entire labor endowment. Denoting the wage rate per effective unit of labor by w, a worker's labor income then is wa.

Skills and technology. Entrepreneurs run firms and collect their firm's profits. Let firm i's "technology" be M_i, and assume that it is defined such that firms with a higher level of

[14] Concave utility would not affect qualitative results. While in general, risk aversion is an important factor affecting entrepreneurial entry (see e.g. Kihlstrom and Laffont 1979, Vereshchagina and Hopenhayn 2009), the mechanism at the heart of this paper does not interact with it. An extension in Section 5 can be interpreted in terms of heterogeneity in risk aversion.

technology, relative to their competitors, are more profitable. Also assume that more able individuals can use better technologies: $M_i = M(a, \cdot)$, with $\partial M(a, \cdot)/\partial a > 0$.[15] For concreteness, suppose that $M = \bar{M}^a$, where $\bar{M} \geq 1$ is a parameter capturing the state of aggregate technology and a is the entrepreneur's ability. Then, the most able entrepreneurs ($a = \bar{a}$) operate at the technological frontier, the least able ones ($a = 0$) at the lowest level, and intermediate ones at some distance to the frontier. Under these assumptions, the position of a firm relative to the frontier, $m(a, \bar{M}) = M(a, \bar{M})/M(\bar{a}, \bar{M}) = \bar{M}^{a-\bar{a}}$, is bounded between 0 and 1. Crucially, for low levels of the frontier, all firms are close to it (and if $\bar{M} = 1$, all firms are at the frontier). The higher the frontier, the more dispersed the levels of technology of potential firms. (Those of actually active firms will depend on occupational choice.)

This specification captures the effect of increasing technological complexity on individual firms: as the frontier advances, some firms can stay close to the frontier and use these better technologies. Other firms can only use some of them, so while they benefit somewhat and use some of the new technologies, their distance to the frontier increases: they benefit in absolute terms, but lose in relative ones. Since more skilled entrepreneurs are the ones who benefit most from technological improvements, this is "skill-biased change in entrepreneurial technology".

In this economy, a population ability distribution will induce occupational choice between working and entrepreneurship, and correspondingly an ability distribution of workers and a productivity distribution of firms.

Firm profits. Firms employ labor in differentiated activities to produce the homogeneous consumption good. A firm's level of technology M_i indicates the number of differentiated activities in a firm and thus corresponds to the complexity of its production process, or the extent of division of labor in the firm. The assumption that more able individuals can run firms with better technology thus concretely means that they can manage more complex production processes, while others are limited to simple ones.[16]

[15] Rosen (1982) also assumes positive correlation of potential profits and wages. Jovanovic (1994) shows that with a different sign of the derivative, radically different occupational choice outcomes are possible. Yet, occupational choice outcomes are quite rich even with the natural assumption in the text.

[16] This appears to be a very natural way of introducing heterogeneity. Galí (1995) uses a similar setup, but allows a representative firms to optimally choose its degree of specialization in production. If stronger specialization is costless, the greatest degree is optimal. This may not be true if it entails costly complexity. Heterogeneity in the cost of complexity would induce different choices of M. Assuming that the cost of managing complexity decreases in a then would induce a qualitatively similar relation between M and a as the more direct assumption made in the text.

A firm's production technology is summarized by the production function

$$y_i = X_i^\gamma, \quad X_i = \left(\int_0^{M_i} n_{ij}^{\frac{\sigma-1}{\sigma}} \mathrm{d}j \right)^{\frac{\sigma}{\sigma-1}}, \quad \gamma \in (0,1), \sigma > 1, \tag{1}$$

where y_i is output of firm i, X_i is an aggregate of the differentiated labor inputs n_{ij} it uses, and M_i indicates the degree of complexity of its technology. The production function exhibits decreasing returns to scale. This can be interpreted to reflect any entrepreneur's limited span of control, as in Lucas (1978). It also ensures that firm size is determinate, implying a firm size distribution given any distribution of M over firms. The elasticity of substitution among inputs is given by σ. Given that M differs across firms and that thus not all firms use all types of differentiated inputs, it is natural to assume that different inputs are substitutes ($\sigma > 1$). Heterogeneity in M plays a role as long as they are imperfect substitutes, as shown below.[17] Importantly, the production function exhibits love of variety, and firms with larger M are more productive. (Therefore, in the following I will sometimes refer to M as "productivity".) An increase in the frontier $\bar{M}$ then increases all firms' productivity, but benefits those close to the frontier the most.

The firm's profit maximization problem can be solved using a typical two-stage approach: choose inputs n_{ij} to minimize the cost of attaining a given level of the input aggregate X, and then choose X to maximize profit. The solution to the latter will depend on a firm's productivity M.

Denoting desired output by $\bar{y}$ and defining $\bar{X} = \bar{y}^{1/\gamma}$, the solution to the cost minimization problem yields the firm's labor demand function for each activity j as

$$n_j(M) = \left(\frac{w}{\lambda_{\bar{X}}} \right)^{-\sigma} \bar{X} \quad \forall j, \tag{2}$$

where λ is the marginal cost of another unit of X. With constant returns to scale for transforming the differentiated labor inputs into X, λ is independent of X and equals $M^{\frac{1}{1-\sigma}} w$, and the demand for each n_j becomes

$$n_j(M) = M^{\frac{-\sigma}{\sigma-1}} \bar{X} \quad \forall j. \tag{3}$$

[17]The formulation in equation (1) is isomorphic to one where final goods firms use (a heterogeneous number of) differentiated intermediate products, intermediates are produced using a production function that is linear in labor, and there is perfect competition in each intermediate goods sector. Monopolistic competition in intermediate goods can also be accommodated easily and would just require a remapping of parameters. In the quantitative exercise in Section 5, a more general specification is chosen in which intermediates are produced using capital and labor with constant returns to scale.

Because of greater specialization in firms using more complex technologies, their marginal cost of X, λ, is lower. As a consequence, they require less of each input to produce $\bar{y}$. Because a larger M allows a firm to produce more output from a given quantity of inputs, I will in the following refer to M as the firm's productivity. While M does not equal TFP, it maps one-to-one with TFP.

Choice of $\bar{X}$ to maximize profits yields optimal output and profits as

$$y(M) = \left(\frac{w}{\gamma}\right)^{\frac{-\gamma}{1-\gamma}} M^{\frac{1}{\sigma-1}\frac{\gamma}{1-\gamma}}, \quad \pi(M) = (1-\gamma)y(M). \tag{4}$$

Both output and profits increase in M. They are convex in M if $\gamma > \frac{\sigma-1}{\sigma}$.[18] As this inequality holds for reasonable sets of parameter values (e.g. $\gamma = 0.9$ and $\sigma < 10$), I will from now on assume that it is satisfied.

Occupational choice. Occupational choice endogenously determines the distributions of workers' ability and of firms' technologies. Since both the firm's and the worker's problem are static, individuals choose to become a worker if $wa > \pi(M(a))$. Given the wage rate, the known value of an agent's ability thus is sufficient for the choice.[19]

Because profits are continuous, increasing and convex in a, while wages are linear in a, it is clear that there is a threshold a_H above which it is optimal to become an entrepreneur. If $a_H < \bar{a}$ (the upper bound on a), high-productivity firms are active in the economy. At the same time, from (4), $\pi(M(0)) > 0 = w \cdot 0$, so that agents with ability between 0 and a threshold a_L become entrepreneurs. In analogy with the evidence reported in Section 2, refer to them as "entrepreneurs out of necessity". Individuals with $a \in (a_L, a_H)$ choose to become workers.

The existence of necessity entrepreneurs is due to the specific way in which technology and its relationship with ability is modelled here and need not arise with other ways of modelling heterogeneity in productivity and its relation to ability. Yet, while the specification chosen here delivers their existence somewhat directly, their occupational choice arises naturally in more general settings with heterogeneity in productivity and pre-entry uncertainty about a project's merits, as shown in Poschke (2010*b*). More precisely, even if expected profits of the lowest-ability potential entrepreneur are zero or negative, this is not what matters because of the ability

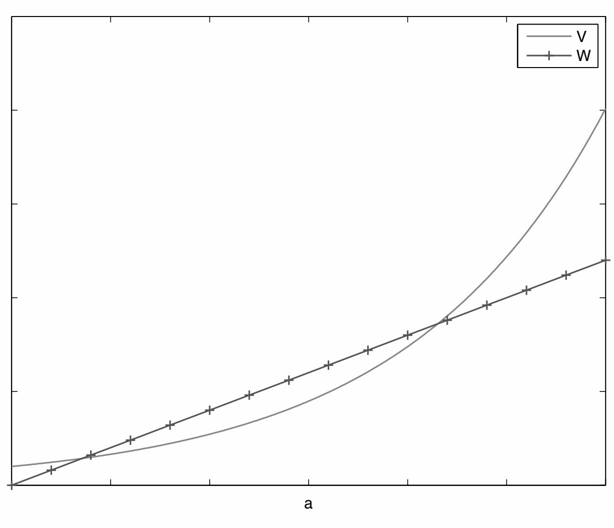
[18] A low γ implies more quickly decreasing returns to scale. As a result, optimal size responds less to productivity, and benefits from being more productive are not as large, implying less convex $\pi(M)$. High σ implies that inputs are more substitutable, so the benefit of being able to use more of them declines.

[19] We abstract from entry costs, sunk investment, search or other issues that would make the problem dynamic without necessarily substantially affecting results. For a related setting with search, see Poschke (2010*b*).

to reject bad projects. Once only sufficiently good projects are accepted, low-ability agents will choose entrepreneurship if projects that are preferred to employment exist and they are sufficiently likely to find them. That paper also provides empirical evidence on the phenomenon of low-ability entrepreneurship and its relationship with potential wages that fits with the setting adopted here.

For $a_H < \bar{a}$, the resulting occupational choice pattern then is as depicted in Figure 3, which plots the value of entrepreneurship (solid line) and of employment (line with crosses) against a. Low- and high-a agents become entrepreneurs, with intermediate-a individuals choosing to become workers.[20] This pattern persists when also considering additional heterogeneity that is orthogonal to that in a, e.g. differences in taste for entrepreneurship or in attitudes towards risk. This two-sided occupational choice pattern fits with evidence on the propensity to be an entrepreneur across the education and wage distribution reported in Poschke (2010*b*). It differs from the pattern usually obtained in this type of model, e.g. the individuals with the highest entrepreneurial ability (Lucas 1978) or the lowest risk aversion (Kihlstrom and Laffont 1979) choosing entrepreneurship. The self-employed in Gollin (2007) also have relatively high entrepreneurial ability and potential wages.

Figure 3: The values of employment ($W(a)$) and entrepreneurship ($V(a)$)



[20]The lower threshold a_L is always interior ($\in (0, \bar{a})$), as otherwise the labor market does not clear.

Equilibrium. An equilibrium of this economy consists in a wage rate w and an allocation of agents to activities such that, taking w as given, agents choose optimally between work and entrepreneurship, firms demand labor optimally, and the labor market clears.

Denoting the density of firms over a by $\nu(a)$, their total measure by B and total effective labor supply by $N \equiv \int_{a_L}^{a_H} a\phi(a)\mathrm{d}a$, the equilibrium wage rate then is obtained from labor market clearing as

$$w = \gamma \left[\frac{B}{N} \int \nu(a) M(a)^{\frac{1}{\sigma-1}\frac{\gamma}{1-\gamma}} \mathrm{d}a \right]^{1-\gamma}. \tag{5}$$

The model is easy to extend to capital as an input, to the production of intermediate goods outside the firm, with perfect or monopolistic competition, and to other dimensions of heterogeneity, e.g. in tastes or in risk aversion. The quantitative exercise in Section 5 will employ such a more general model.

4 Development and the firm size distribution

In this model, technological improvements affect occupational choice and, through this channel, the firm size distribution.

4.1 The technological frontier and occupational choice

Changes in the technological frontier affect incentives to become a worker or an entrepreneur both through their effect on potential profits and on wages. As technology advances, some firms stay close to the advancing frontier, while others fall behind. As a result, profits as a function of ability change, the populations of firms and workers change, and the equilibrium wage rate changes. Using $M(a, \bar{M}) = \bar{M}^a$, recall that profits and the wage are given by

$$\pi(a, \bar{M}) = (1-\gamma) \left(\frac{w}{\gamma} \right)^{\frac{-\gamma}{1-\gamma}} \bar{M}^{\eta a} \tag{6}$$

$$w(\bar{M}) = \gamma \left[\frac{B}{N} \int \nu(a) \bar{M}^{\eta a} \mathrm{d}a \right]^{1-\gamma}, \tag{7}$$

where $\eta \equiv \frac{1}{\sigma-1}\frac{\gamma}{1-\gamma} > 1$. To see the effect of advances in the technological frontier, consider their elasticities with respect to $\bar{M}$.

$$\varepsilon(\pi(\cdot), \bar{M}) = \eta a - \frac{\gamma}{1-\gamma} \varepsilon(w, \bar{M}) \tag{8}$$

$$\varepsilon(w(\cdot), \bar{M}) = \frac{\gamma}{\sigma-1} \int \nu(a) a \bar{M}^{\eta a} \mathrm{d}a \left[\int \nu(a) \bar{M}^{\eta a} \mathrm{d}a \right]^{-1} \tag{9}$$

An advance in the frontier has two effects on profits: it improves every firm's technology (the first term), but it also raises the wage rate (the second term), which is a drag on profits. As the effect of higher wages is independent of a, it is clear that only firms with high enough a benefit from aggregate technology improvements. Low-a firms lose more to the wage increase than they gain from the productivity improvement. Wages, in contrast, unambiguously increase with advances in the technological frontier. As a consequence, the composition of the firm size distribution changes as technology advances.

Note that if all agents had the same ability a, both $\varepsilon(w, \bar{M})$ and $\varepsilon(\pi(a), \bar{M})$ would reduce to $\frac{a\gamma}{\sigma-1}$. As a consequence, wages and profits would increase in sync with technological advances, and occupational choice would remain unaffected, i.e. the thresholds a_L and a_H constant. Only with heterogeneity in a do some agents benefit more than others from advances in the frontier, and occupational choices change.

For an individual with ability a, an improvement in the frontier makes becoming an entrepreneur relatively more attractive if

$$\Delta\varepsilon(a, \bar{M}) \equiv \varepsilon(\pi(\cdot), \bar{M}) - \varepsilon(w(\cdot), \bar{M}) = \eta a - \eta \int \nu(a) a \bar{M}^{a\eta} \mathrm{d}a \left[\int \nu(a) \bar{M}^{a\eta} \mathrm{d}a \right]^{-1} > 0. \quad (10)$$

Advances in the frontier thus affect the occupational choices of agents of different ability differently. For the most productive entrepreneurs ($a = \bar{a}$), $\Delta\varepsilon(\cdot)$ will always be positive. This is because for $a \in (0, \bar{a}]$ and for any $\nu(a)$, both integrals in (10) are strictly positive. In addition, $a\bar{M}^{\eta a}/\bar{M}^{\eta a} < \bar{a}$ for $a \in [0, \bar{a})$, implying that the ratio of integrals is between 0 and $\bar{a}$. Similarly, $\Delta\varepsilon$ is strictly negative for the worst entrepreneurs. This implies that as the technological frontier advances, the best entrepreneurs gain, and the worst ones lose.

Intuitively, whether a firm gains or loses depends on its productivity relative to a complicated moment of the productivity distribution. This is because advances in the frontier increase labor demand and wages, and thereby all firms' costs. They also improve firms' productivity – but only firms that can make use of most of the advance in the frontier benefit sufficiently from this. Low-a firms that benefit only slightly from advances in the frontier are exposed to the wage increase, while their own productivity improves only mildly.

What is more, as the frontier continues to advance, the winners become more concentrated. This is because

$$\frac{\partial \Delta\varepsilon}{\partial \bar{M}} = -\frac{\eta^2}{\bar{M}} \frac{\int \nu(a) \bar{M}^{a\eta} \mathrm{d}a \int \nu(a) a^2 \bar{M}^{a\eta} \mathrm{d}a - [\int \nu(a) a \bar{M}^{a\eta} \mathrm{d}a]^2}{[\int \nu(a) \bar{M}^{a\eta} \mathrm{d}a]^2} < 0. \quad (11)$$

This implies that even firms that at low levels of $\bar{M}$ benefit from increases in the frontier see these benefits reduced and eventually turn negative as the frontier advances further. Only for firms with $a = 1$ is it certain that $\Delta\varepsilon$ cannot turn negative. For firms with $a = 0$, in contrast, it is always negative. For high enough a, $\Delta\varepsilon$ is positive for low $\bar{M}$, eventually turns negative and ultimately pushes $\pi(a, \bar{M})$ below wa. The next section explores the evolution of occupational choice as captured by a_L and a_H and its implications for the firm size distribution and entrepreneurship.

4.2 A "history" of entrepreneurship and the firm size distribution

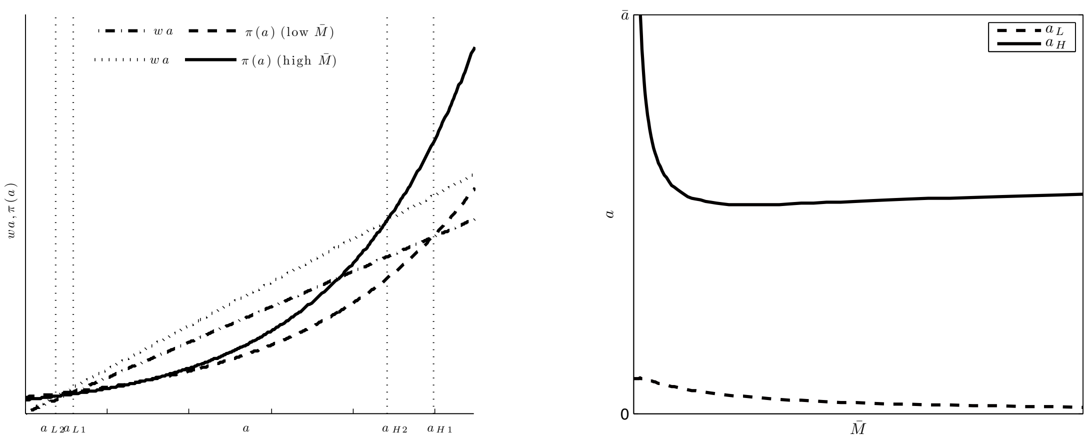
Historically, every successful development experience has been characterized by improvements in total factor productivity. This section explores the predictions of the model for occupational choice and the firm size distribution along a "history" of an advancing technological frontier. As the model is static, every $\bar{M}$ induces an equilibrium occupational choice, summarized by the thresholds a_L and a_H, and a firm productivity distribution implied by these choices. Let $\bar{\mathbf{M}} = \{\bar{M}_0, \bar{M}_1, \ldots, \bar{M}_T\}$, $\bar{M}_0 = 1$, be a strictly increasing sequence of real numbers and refer to it as the history of $\bar{M}$. Analyzing the equilibrium of the model economy for each element of $\bar{\mathbf{M}}$ then yields a "history" of occupational choice and the firm size distribution.[21]

The sequence $\bar{\mathbf{M}}$ can also be interpreted as a list of different countries' technological states at a point in time. It then induces a cross-section of occupational choices and firm size distributions. This interpretation is pursued in the next section. To evaluate the quantitative fit, the model is slightly extended and calibrated in that section. This is not necessary for the qualitative history explored in the present section.

Figure 4 shows the evolution of occupational choice as $\bar{M}$ increases. The left panel shows profits and wages as functions of ability for two levels of $\bar{M}$. As in Figure 3, the straight lines correspond to wages and the curved ones to profits, and a_{Li} and a_{Hi} $(i = 1, 2)$ indicate the choice thresholds.

The left panel illustrates how occupational choice changes with $\bar{M}$. Higher $\bar{M}$ raises the productivity of all firms and thereby leads to higher wages: the wage line pivots up from the straight dash-dot line to the straight dotted line. Higher productivity raises profits (they change from the dashed to the solid line), except for some firms of low-a entrepreneurs for who the pro-

[21] An alternative is to consider a history where $\bar{M}_t$ grows over time at an exogenous rate g. This is particularly relevant in the context of the extension with capital used in the next section. While growth in $\bar{M}$ leads to changes in occupational choice and in the share of entrepreneurs, the setting is consistent with balanced growth since increases in $\bar{M}$ constitute labor-augmenting technical progress and the aggregate production function exhibits constant returns to scale (King, Plosser and Rebelo 1988). Results in this section can thus also be interpreted as developments along the balanced growth path of an economy.



(a) Occupational choice for two values of $\bar{M}$

(b) The evolution of the thresholds a_L and a_H with increasing $\bar{M}$

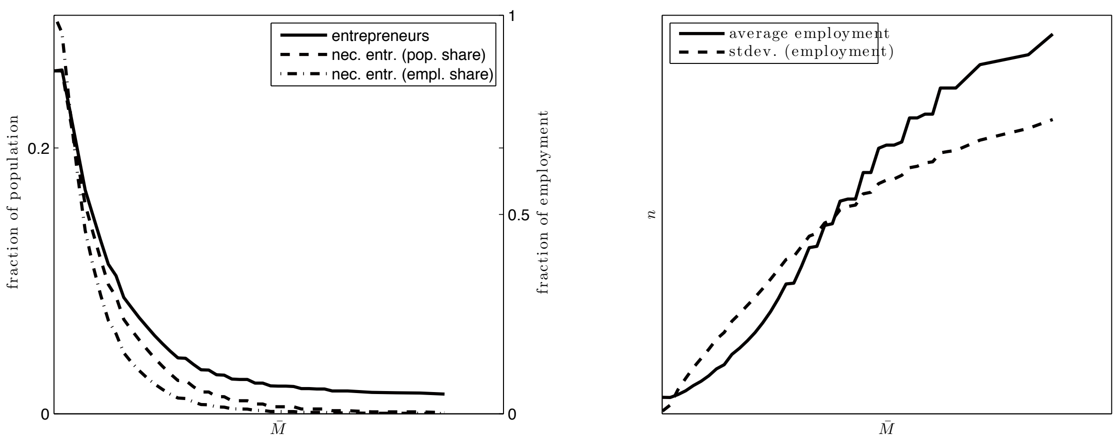
Figure 4: Occupational choice as $\bar{M}$ increases

ductivity increase is so small that it is outweighed by the increase in wages. This unambiguously makes entrepreneurship more attractive for the highest-ability agents, and less so for the ones with the lowest ability. In the situation drawn in the figure, entrepreneurs with a just below a_{H1} still benefit and agents at or just below a_{L1} lose from higher $\bar{M}$. As a result, a_H falls from a_{H1} to a_{H2}, and a_L falls from a_{L1} to a_{L2}. It is mainly higher labor demand from top firms and the entry of new relatively productive firms between a_{H1} and a_{H2} that drives wages up.

The right panel shows the values taken by a_L and a_H for a "history" of increasing $\bar{M}$. Starting from low $\bar{M}$, increases in $\bar{M}$ reduce both a_H and a_L, as in the left panel of the figure. Once most low-productivity firms are gone, firms with $a = a_H$, while run by relatively high-ability individuals, actually have low productivity compared to other firms in the economy. From this point on, further advances in $\bar{M}$ raise profits less than wages for firms with $a = a_H$, and the upper threshold a_H shifts up again. (Formally, this is because $\Delta\varepsilon(a_H, \bar{M})$ as defined in equation (10) turns negative with increasing $\bar{M}$, as shown in equation (11).) As $\bar{M}$ increases further, a_L falls further, but approaches zero only asymptotically. The upper threshold a_H also continues to rise, albeit at a slow pace. ($\partial\Delta\varepsilon(a, \bar{M})/\partial\bar{M}$, while always negative for $a < \bar{a}$, falls in absolute value as $\bar{M}$ increases.) As a result, for very high levels of the frontier, almost all active firms have high productivity.

Advancing technology does not lift all boats here. By assumption, the most able agents benefit most from advances in the technological frontier, as they can deal more easily with the increased complexity and use a larger fraction of the new technologies. Low-ability entrepreneurs benefit less. In fact, increasing wages due to higher productivity at top firms (wage earners always gain from technological improvements) mean that the least productive firms' profits fall as technology improves. As a consequence, marginal low-productivity entrepreneurs convert to become wage earners, and eventually also do better, though not necessarily immediately. The lowest-ability agents ($a = 0$) always lose. Technology improvements thus have a negative effect on low-productivity firms that operates through wage increases.

Figure 5(a) depicts the consequences of this development: the entrepreneurship rate (solid) falls as technology improves. While high-productivity firms replace the exiting low-productivity ones, they operate at a larger scale, so their number is smaller. Similarly, the shares of necessity entrepreneurs (defined as $a < a_L$, dashed line) and employment in their firms (dash-dot line, right axis) fall and ultimately go to zero.



(a) The entrepreneurship rate

(b) Average firm size and firm size dispersion

Figure 5: Model "time series"

This development in the model parallels the evidence from Section 2, which reported entrepreneurship rates and rates of necessity entrepreneurship that fall in income across countries and in U.S. history. The model also replicates observed patterns in average firm size (solid line in Figure 5(b)). If some agents are better placed than others to benefit from technological advances, they drive others out of the market. As a consequence, marginal small firms exit, average firm size grows (solid line), and fewer, more productive firms remain. Only a few necessity entrepreneurs remain active.

At the same time, firm size dispersion increases. (The figure shows the standard deviation of employment, dashed line.) This has two sources. Firstly, for any fixed thresholds a_L and a_H, increases in $\bar{M}$ imply increasing dispersion in productivity and therefore in employment. On top of that, entry of very productive firms increases dispersion – as long there are small firms around. As their proportion falls with development, this driver weakens, explaining the concavity of the line in the figure.[22]

Of course, there currently still are small firms in rich countries like the U.S.. Possible reasons for this are that empirically, $\bar{M}$ only takes on an intermediate value, that other factors such as tastes also matter, implying that some small firms remain active despite their low productivity (the quantitative exercise in the next section allows for this), or that in some industries or markets returns to scale decrease very quickly, implying a less convex (in a and $\bar{M}$) profit function and longer activity of low-productivity firms.

Summarizing the model "time series", the model thus is consistent with the facts reported in Section 2 that the entrepreneurship rate and the share of necessity entrepreneurs fall with per capita income and that average firm size and firm size dispersion increase with per capita income.

5 Quantitative exercise: occupational choice and entrepreneurship across countries

How well do the historical experience of one country and cross-country patterns accord? This is a test of how relevant the mechanisms in the model are relative to other factors affecting entrepreneurship and the firm size distribution.

To explore this, I calibrate the model to the U.S. experience and then evaluate how well it fits across a broad set of countries; in particular, how well it mimics the empirical relationships shown in Section 2.

[22] How does this fit with Hsieh and Klenow's (2009) finding of larger TFP dispersion in China than in the U.S. (keeping in mind the measurement issues discussed in footnote 13)? The long left tail of the Chinese productivity distribution visible in their Figure I suggests a large distortion of the entry and exit margin when seen through the lens of standard heterogeneous firm models (Hopenhayn (1992); see also Samaniego (2006), Barseghyan (2008), Poschke (forthcoming) and Moscoso Boedo and Mukoyama (2010)). Given that their high size cutoff probably excludes from their data almost all the rather small firms run by necessity entrepreneurs, this corresponds to a downward distortion of a_H in the present context. If this distortion is large in a poor country, the model can generate higher productivity dispersion of firms with $a > a_H$ in the poorer country. Dispersion computed using firms of all sizes will however still be larger in the richer country, as it is in the GEM data.

5.1 Generalized model

For the quantitative exercise, it is useful to generalize the very stylized model from Section 3 slightly. I introduce three modifications: production of intermediates with capital and labor, heterogeneity in taste for entrepreneurship, and a more general specification of $M(a)$.

Capital. In the simple model in Section 3, the differentiated activities used for producing final output use labor only. The aggregate input X has constant returns to scale in all labor inputs. Replace this by

$$X = \left(\int_0^{M_i} (n_j^{\alpha} k_j^{1-\alpha})^{\frac{\sigma-1}{\sigma}} \mathrm{d}j \right)^{\frac{\sigma}{\sigma-1}}, \tag{12}$$

i.e., production of intermediates with capital and labor. This allows setting α and γ to match income shares in the data. Firms' optimization is as in Section 3, taking the wage rate w and the rental rate of capital r as given. Households, who own the capital stock and rent it to firms, now face a capital accumulation decision. Their Euler equation, evaluated at the steady state of the economy they live in (thus, given its $\bar{M}$), prescribes equating the rental rate of capital net of depreciation to the rate of time preference. Assuming a common rate of time preference ρ and a common depreciation rate δ, this implies $r = \rho + \delta$. The firm's optimality condition for capital then pins down the aggregate capital stock.

Taste heterogeneity. In the model of Section 3, only agents with $a < a_L$ or $a > a_H$ become entrepreneurs. Given the one-to-one mapping between a and M, this implies a bimodal firm size distribution with only low- and high-productivity firms, but no firms with intermediate productivity. This is clearly counterfactual. Incorporating heterogeneity in tastes for entrepreneurship into the model allows to "fill in" the hole in the middle of the firm size distribution, while also adding realism. Indeed, most empirical studies of entrepreneurship point to some role for heterogeneity in tastes or risk aversion for entrepreneurship (see e.g. Hamilton 2000).

Thus, suppose that agents differ in their taste for entrepreneurship τ. Define this such that individuals choose entrepreneurship if $\tau\pi(a) > w \cdot a$. $\tau > 1$ then implies "enjoyment" of entrepreneurship. If agents enjoy entrepreneurship, they will choose it even if $\pi(a) < w \cdot a$. Whether on average agents enjoy entrepreneurship is an empirical question; therefore the distribution of τ has to be calibrated, and the mean could be different from 1. A mean below 1 indicates that on average, individuals do not enjoy entrepreneurship.

With this additional dimension of heterogeneity, there are entrepreneurs of all levels of ability, and the productivity distribution can be unimodal if the ability distribution is so. However, individuals of high or low ability are still more likely to become entrepreneurs. Changes in $\bar{M}$ shift the relationship of $\pi(a)$ and wa and therefore the taste threshold for entering entrepreneurship, resulting in an evolution of the proportion of agents with a given a who are entrepreneurs.[23]

Heterogeneity in risk aversion combined with a simple extension of the model would yield similar results. Suppose that wage income is certain and equals wa every period. Business income is a function of the entrepreneur's ability and of an *iid* shock every period. (This reflects the higher variance of income from entrepreneurship; fluctuating wages could easily be accommodated, too.) Define the shock such that profits are given by $s_t\pi(a), \ln s_t \sim N(0, \sigma_\pi^2)$. Let the period utility function be $u(c) = c^{1-\rho}/(1-\rho)$, where the coefficient of relative risk aversion ρ can vary across people. Then period utility from working is $(wa)^{1-\rho}/(1-\rho)$, and expected period utility from entrepreneurship is $\mathbb{E}(s_t\pi(a))^{1-\rho}/(1-\rho) = \pi(a)^{1-\rho}\exp((1-\rho)^2\sigma_\pi^2/2)/(1-\rho)$. Entrepreneurship thus is preferred if $(e^{\sigma_\pi^2/2})^{1-\rho}\pi(a) > wa$. The term $(e^{\sigma_\pi^2/2})^{1-\rho}$ here plays the same role as the taste parameter τ above: Higher risk aversion ρ or variance of profits σ_π^2 make entrepreneurship less attractive. The parametrization of heterogeneity in τ in the next section can thus alternatively be interpreted as describing variation in risk aversion. Because the setting with risk aversion contains more free parameters and also raises issues of the dynamic behavior of profits, I will pursue the taste interpretation in the remainder of the paper.

The technological frontier and complexity. How much additional complexity do advances in the technological frontier comport? The simple specification of $M(a)$ chosen in Section 3 restricted this relationship. But it is of course an empirical issue. Therefore, in this section, let a firm's technology be given by

$$M(a, \bar{M}) = \bar{M}^{\frac{a-\lambda}{\lambda}}, \tag{13}$$

[23] With heterogeneity in a only, it is reasonable to define necessity entrepreneurs as those with $a < a_L$, as in Section 4.2. With two dimensions of heterogeneity, there can be entrepreneurs of all levels of a, so a different definition is needed. I base this on characteristics of necessity entrepreneurs in the data and on the wording of the survey question. First of all, in the GEM data, no owner of a large firm declares being a necessity entrepreneur. I therefore never consider entrepreneurs running a firm with more than 5 times average employment as necessity entrepreneurs. Secondly, the survey question suggests that necessity entrepreneurs choose this occupation because it yields more income than the alternatives and not out of enjoyment. I thus impose $\pi > wa$ as a second criterion; excluding entrepreneurs who chose their occupation because of high τ.

implying that its position relative to the frontier is

$$m(a, \bar{M}) = \frac{M(a, \bar{M})}{M(\bar{a}, \bar{M})} = \bar{M}^{\frac{a-\bar{a}}{\lambda}}. \tag{14}$$

The lower λ, the faster low-ability entrepreneurs fall behind the technological frontier as it advances. Note that this relationship contains two parameters: λ and $\bar{M}$, which is an important parameter in its own right. They enter equation (13) sufficiently differently that both can be calibrated, using information from the U.S. time series.

5.2 Calibration

The model is calibrated to U.S. data. Some parameters can be set using standard numbers from the literature, while the remaining ones are calibrated to match a set of moments describing the U.S. economy. Note in particular that $\bar{M}$ has important effects on endogenous variables and can therefore be calibrated using U.S. data.

The share parameters γ and α are set to generate a profit share of income of 10% and a labor share of two thirds. This implies a γ of 0.9 and an α of 0.74. The elasticity of substitution among intermediate inputs is set to 4, which is about the 75th percentile of the distribution of σ across 4-digit industries estimated by Broda and Weinstein (2006).[24] Setting the rate of time preference to 4% and the depreciation rate to 10% per annum implies a rental rate of capital of 14%.

For the remaining parameters, first suppose that the ability and taste distributions are lognormal. A lognormal ability distribution implies that the wage distribution would be lognormal if everyone was an employee. With taste heterogeneity, entrepreneurs will come from across the ability distribution, and the wage distribution will be close to lognormal. For tastes, a lognormal distribution also seems natural, as they affect payoffs multiplicatively. Letting $\ln a \sim N(\mu_a, \sigma_a)$ and $\ln \tau \sim N(\mu_\tau, \sigma_\tau)$, the remaining moments to be calibrated are $\mu_a, \sigma_a, \mu_\tau, \sigma_\tau, \lambda$ and $\bar{M}$.

Data and model moments are shown in Table 1. U.S. data is for the year 2000, or close years where that year is not available. To pin down the parameters, information about the firm size distribution, about the distribution of wages and about the link between the two is needed. Targets are chosen accordingly:[25] Average employment (from the Census Statistics of U.S. Businesses (SUSB)) and the rate of necessity entrepreneurship (from the GEM) are

[24] Results are robust to setting σ substantially higher, to 6. This is although the sensitivity of profits with respect to $\bar{M}$ declines with σ (see e.g. equation (4)).

[25] In fact, the six parameters have to be calibrated jointly. While the following discussion stresses the main informational contribution of individual targets, parameters and target choices actually interact.

informative about μ_a and μ_τ. Wage inequality, measured as the ratio between the 90th and the 10th percentile of the wage distribution, is taken from Autor, Katz and Kearney (2008, Figure 2.A) and helps to pin down σ_a. Changes in σ_τ affect occupational choice and thereby both the wage and the distribution of profits. A statistic that links the two is the fraction of firms with profits smaller than the average wage, taken from Hamilton (2000, Figure 1 and Table 3). As seen in the previous section, the level of $\bar{M}$ also affects the dispersion of the firm size distribution. To capture this, I target the interquartile range standardized by mean firm size (Census SUSB). This is a measure of dispersion that is robust to outliers, something especially important with a distribution that is as skewed as the firm size distribution.[26]

Finally, to separate λ and $\bar{M}$, information on changes over time is needed. It would be most straightforward to use e.g. average firm size in 1900 in addition to average firm size in 2000, but there is no single series that encompasses both dates. An alternative is to use the elasticity of average firm size with respect to output per worker. This can be computed using any of the four average firm size series plotted in Figure 2(a). They imply elasticities between 0.12 and 0.57. While the Dun & Bradstreet series is longest (1890-1983), the figure suggests that it may overstate the increase in average firm size in the post-war period. To be conservative, I therefore target an elasticity of 0.34, which is in the middle of the range in the data. Moreover, this value is close to the ones implied by the recent SUSB series (1988-2006) and by the BEA Survey of Current Business series when omitting the Great Depression years.

[26]Many thanks to Lori Bowan at the Census Bureau for providing a table with 1997 firm counts in detailed size categories.

Table 1: Calibration: Data and model moments

	model	data
average employment $\bar{n}$ (2000)	19.8	20
firm size iqr/$\bar{n}$	0.29	0.30
fraction firms with $\pi < \bar{w}$	0.63	0.67
share necessity entrepreneurs	0.13	0.13
ln 90/10 wage ratio	1.68	1.66
$\varepsilon(\bar{n}, Y)$	0.34	0.34

Sources for data moments: average firm size and interquartile range (iqr) from Census Statistics of U.S. Businesses (SUSB) tabulations; fraction firms with $\pi < \bar{w}$ from Hamilton (2000); share of necessity entrepreneurship from GEM, see Section 2.1; wage ratio from Autor et al. (2008, Figure 2A); elasticity of average employment with respect to output per worker uses average firm size data plotted in Figure 2(a) combined with data on non-farm employment from the BLS and from Weir (1992, Table D3), reprinted in Carter et al. (2006), and data on non-farm output from the BEA (`http://www.bea.gov/bea`, Table 1.3.6) and from U.S. Department of Commerce (1975, Series F128).

Values of the calibrated parameters are reported in Table 2. On average, individuals do not like entrepreneurship (the implied average τ in the population is clearly below 1), and thus require a premium before they take it up. There is substantial variation, however. Also note that the $\bar{M}$ resulting from the calibration describes the U.S. level of technology in 2000. To evaluate cross-country patterns, it will be necessary to set other countries' $\bar{M}$ relative to the U.S. level such that the output ratios match the data. The model-generated "time series" of average employment in the U.S. is plotted against non-farm output per worker in Figure 6. As the calibration fits the observed elasticity of 0.34 well, the series of average employment also fits well.

Table 2: Calibrated parameter values

from external sources:					
γ	α	σ	ρ	δ	
0.9	0.74	4	0.04	0.1	
from fitting U.S. target moments:					
μ_a	σ_a	μ_τ	σ_τ	λ	$\bar{M}$
-0.5792	0.66528	-4.3191	2.4848	13.5080	783.9069

An interesting dimension that has not been targeted in the calibration is the evolution of income inequality. Overall income inequality in the model increases more than wage inequality,

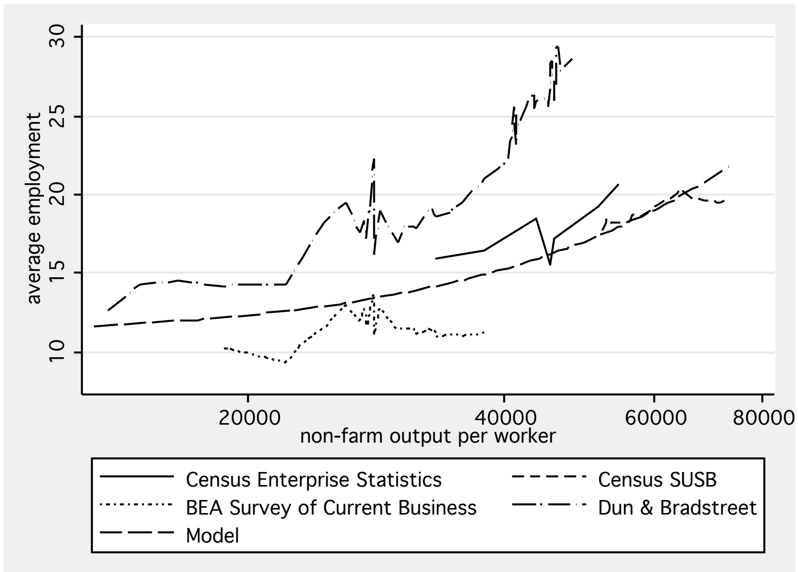


Figure 6: Average firm employment over U.S. history, data and model

as entrepreneurs' incomes lie at the extremes of the income distribution. Figure 7 reports the income shares of the top 10% and 1% in the U.S. income distribution for the data (from Piketty and Saez 2006, for 1950-2002) and for the model, plotted against U.S. GDP per capita relative to its level in 2002. It is not surprising that inequality in the model does not reach its level in the data, as the model has no mechanism generating a fat right tail of the income distribution. What is remarkable, however, is that the trend in the model essentially replicates the trend in the data. For instance, from the mid-1960s to 2002, the income share of the top 1% increased by 6.6 percentage points. The model captures three quarters of this increase. It only misses the jump in U.S. income inequality that is known to have occurred in the 1980s (at about 75% of 2002 GDP per capita).

5.3 Results

The model fits the U.S. experience quite well. To evaluate the fit with other countries, each country is assigned the $\bar{M}$ that replicates the output per capita ratio to the U.S. observed in the data. This $\bar{M}$ is then taken to be the country's state of technology. Figure 8 plots the entrepreneurship rate, average firm size, firm size dispersion and share of necessity entrepreneurs generated by the model for these levels of $\bar{M}$ against the data. The straight line in each graph is the OLS fit discussed in Section 2. The slightly curved lines are the outcomes generated by

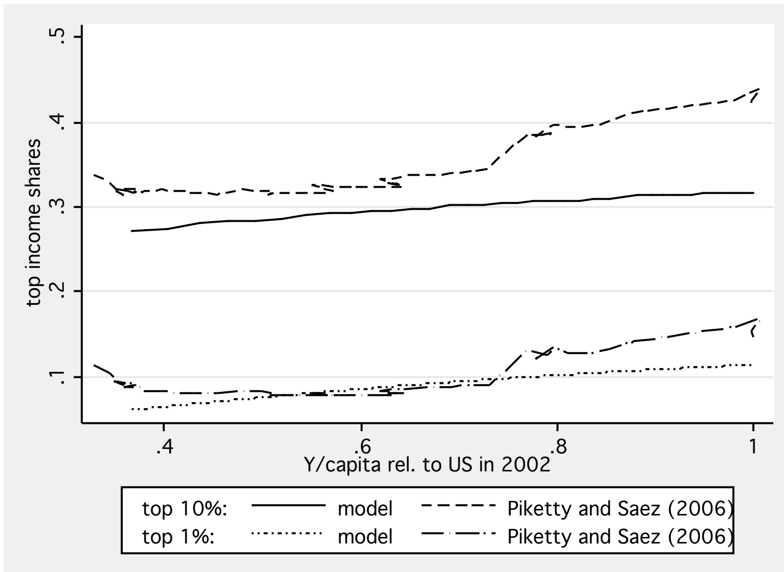


Figure 7: Income concentration at the top, U.S., 1950-2002, model and data

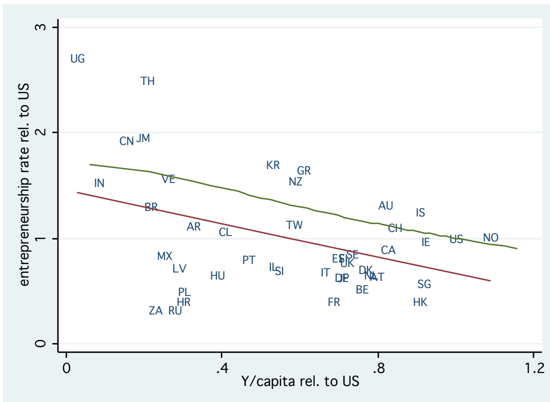
Source: Piketty and Saez (2006).

the model.

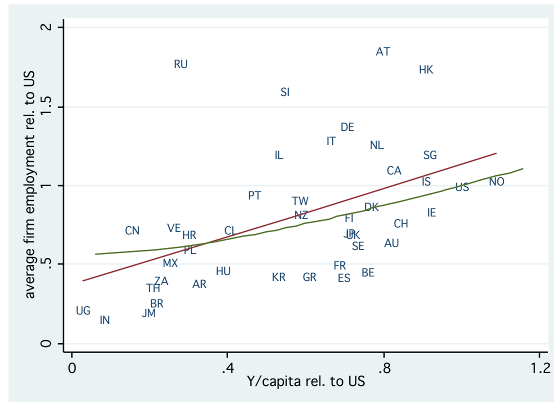
Given that it was calibrated to the U.S., the model fits the cross-country experience rather well. Of course, as shown in Section 4, it predicts that the entrepreneurship rate and necessity entrepreneurship fall with per capita income, while average firm size and the dispersion of firm size increase with it.

Strikingly for such a stylized model, however, the quantitative performance is quite good. The predicted change in the entrepreneurship rate with per capita income has exactly the right slope. The level is somewhat off just because the calibration forces it to pass through the U.S. data point. The prediction for average employment also fits well.

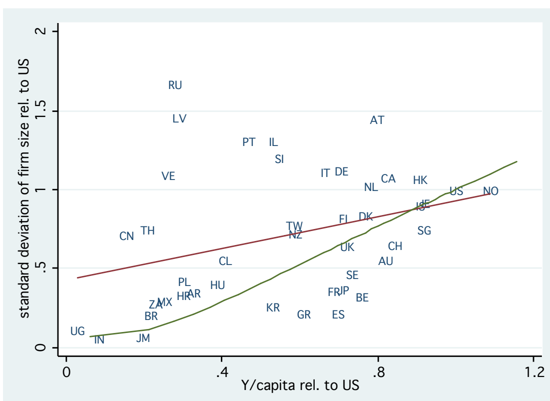
The model overpredicts the sensitivity of firm size dispersion and the share of necessity entrepreneurship with respect to per capita income. The model predictions are a bit too extreme in these two dimensions, with too many necessity entrepreneurs in very poor countries. Their dominance and the fact that skill differences do not affect optimal firm size much for low levels of technology imply too little firm size dispersion at this income level. Note however that in some poor countries, measured firm size dispersion may be inflated by government policy promoting certain firms. The model of course cannot pick this up. Indeed, the model predictions miss some countries where these interventions are known to be important, such as China, as well as



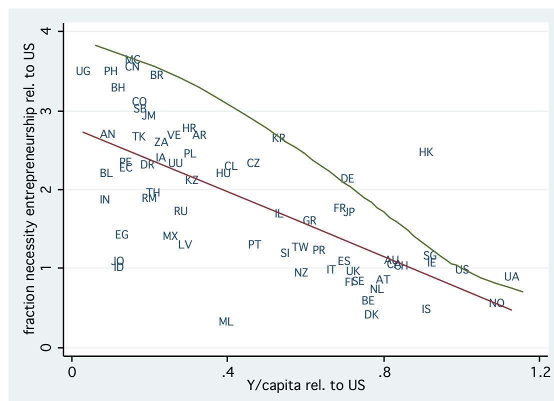
(a) The entrepreneurship rate



(b) Average employment



(c) Firm size dispersion



(d) Fraction necessity entrepreneurs

Figure 8: Entrepreneurship and the firm size distribution versus output per capita (relative to the U.S. levels): model (green curved line) and data (red line: OLS fit)

Notes: Data sources as in Figure 1.

the transition economies of Russia and Latvia. In contrast, the prediction fits quite well with the experience of many other poor countries.[27]

[27]Can the model explain the positive relationship between the density of *registered* businesses and income observed in e.g. the World Bank Group Entrepreneurship Survey data? Suppose that businesses above a certain size threshold find it optimal to register. This would be observed if the benefits of doing so increase more quickly with size than registration costs. (Indeed, empirical work long identified the informal sector with small firms with for instance less than 20 workers; see e.g. Rauch (1991).) Although the effect of $\bar{M}$ on a_L and a_H implies that the proportion of large firms increases with income in the model, the fraction of the population running a firm above a certain size does not necessarily do so because of the accompanying fall in the entrepreneurship rate. The net effect of the two depends on the level of $\bar{M}$ and on the size threshold; e.g. in the model calibration, the population fraction running firms with more than 50 workers increases up to about the U.S. level of $\bar{M}$ and then declines. The model can of course generate the relationship between business registration and income if registration costs are higher in poor countries, as documented by Djankov, La Porta, Lopez-de-Silanes and Shleifer (2002).

6 Conclusion

Despite the existence of a large literature on the effects of technological change, its effects on entrepreneurial entry and its aggregate implications have not received much attention. To address this gap, this paper proposed a very simple model based on skill-biased change in entrepreneurial technology, or the idea that the benefits from technological progress may be larger for more skilled entrepreneurs. The model fits well with U.S. historical evidence and, when calibrated to the U.S., even explains cross-country variation in a broad dataset well. This is despite the simplicity of the model, with technology as the only driver of cross-country differences and abstracting from other factors such as risk or financial constraints. Linking these to the mechanism explored here may make for exciting future work. Skill-biased change in entrepreneurial technology may thus constitute an important determinant of entrepreneurial choice and the firm size distribution, helping to explain differences both over time and across countries.

References

Acs, Z. J., Desai, S. and Klapper, L. (2008), 'What Does "Entrepreneurship" Data Really Show?', *Small Business Economics* **31**, 265–281.

Ardagna, S. and Lusardi, A. (2008), 'Explaining international differences in entrepreneurship: The role of individual characteristics and regulatory constraints', *NBER Working Paper* **14012**.

Autor, D. H., Katz, L. F. and Kearney, M. S. (2008), 'Trends in US wage inequality: revising the revisionists', *Review of Economics and Statistics* **90**(2), 300–323.

Aw, B.-Y. (2002), 'Productivity dynamics of small and medium enterprises in Taiwan', *Small Business Economics* **18**(1), 69–84.

Banerjee, A. V. and Newman, A. F. (1993), 'Occupational Choice and the Process of Development', *Journal of Political Economy* **101**(2), 274–298.

Barseghyan, L. (2008), 'Entry Costs and Cross-Country Differences in Productivity and Output', *Journal of Economic Growth* **13**(2), 145–167.

Bartelsman, E., Haltiwanger, J. and Scarpetta, S. (2004), 'Microeconomic Evidence of Creative Destruction in Industrial and Developing Countries', *World Bank Policy Research Working Paper* **3464**.

Berry, A., Rodriguez, E. and Sandee, H. (2002), 'Firm and group dynamics in the small and medium enterprise sector in Indonesia', *Small Business Economics* **18**(1), 141–161.

Bertrand, M. (2009), 'CEOs', *Annual Review of Economics* **1**.

Blau, D. M. (1987), 'A time-series analysis of self-employment in the United States', *Journal of Political Economy* **95**(3), 445–467.

Broda, C. and Weinstein, D. E. (2006), 'Globalization and the Gains from Variety', *Quarterly Journal of Economics* **121**(2), 541–585.

Cagetti, M. and De Nardi, M. (2006), 'Entrepreneurship, Frictions, and Wealth', *Journal of Political Economy* **114**(5), 835–870.

Cain, L. P. and Paterson, D. G. (1986), 'Biased Technical Change, Scale, and Factor Substitution in American Industry, 18501919', *Journal of Economic History* **46**, 153–164.

Carter, S. B., Gartner, S. S., Haines, M. R., Olmstead, A. L., Sutch, R. and Wright, G., eds (2006), *Historical Statistics of the United States: Millennial Edition*, Cambridge University Press, Cambridge.

Caselli, F. (2005), Accounting for Cross-Country Income Differences, *in* P. Aghion and S. N. Durlauf, eds, 'Handbook of Economic Growth', North Holland, Amsterdam.

Cummins, J. G. and Violante, G. L. (2002), 'Investment-Specific Technical Change in the United States (1947-2000): Measurement and Macroeconomic Consequences', *Review of Economic Dynamics* **5**(2), 243–284.

Djankov, S., La Porta, R., Lopez-de-Silanes, F. and Shleifer, A. (2002), 'The Regulation of Entry', *Quarterly Journal of Economics* **117**(1), 1–37.

Frydman, C. (2007), 'Rising Through the Ranks: The evolution of the market for corporate executives, 1936-2003', *mimeo, MIT* .

Gabaix, X. and Landier, A. (2008), 'Why Has CEO Pay Increased So Much?', *Quarterly Journal of Economics* **123**(1), 49–100.

Galí, J. (1995), 'Product diversity, endogenous markups, and development traps', *Journal of Monetary Economics* **36**(1), 39–63.

Garicano, L. (2000), 'Hierarchies and the Organization of Knowledge in Production', *Journal of Political Economy* **108**(5), 874–904.

Gollin, D. (2007), 'Nobody's business but my own: Self-employment and small enterprise in economic development', *Journal of Monetary Economics* **55**(2), 219–233.

Greenwood, J., Hercowitz, Z. and Krusell, P. (1997), 'Long-run implications of investment-specific technological change', *American Economic Review* **87**(3), 342–362.

Hamilton, B. H. (2000), 'Does Entrepreneurship Pay? An Empirical Analysis of the Returns to Self-Employment', *Journal of Political Economy* **108**(3), 604–631.

Heston, A., Summers, R. and Aten, B. (2009), 'Penn World Table Version 6.3', *Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania* .

Hipple, S. (2004), 'Self-employment in the United States: an update', *Monthly Labor Review* **127**(7), 13–23.

Hopenhayn, H. (1992), 'Entry, Exit, and Firm Dynamics in Long Run Equilibrium', *Econometrica* **60**(5), 1127–1150.

Hornstein, A., Krusell, P. and Violante, G. (2005), The Effects of Technical Change on Labor Market Inequalities, *in* P. Aghion and S. N. Durlauf, eds, 'Handbook of Economic Growth', Vol. 1, Elsevier, Amsterdam, pp. 1275–1370.

Hsieh, C.-T. and Klenow, P. J. (2009), 'Misallocation and Manufacturing TFP in China and India', *Quarterly Journal of Economics* **124**, 1403–1448.

James, J. A. and Skinner, J. S. (1985), 'The Resolution of the Labor-Scarcity Paradox', *Journal of Economic History* **45**, 513–540.

Jovanovic, B. (1994), 'Firm Formation with Heterogeneous Management and Labor Skills', *Small Business Economics* **6**, 185–191.

Jovanovic, B. and Rousseau, P. L. (2008), 'Specific capital and technological variety', *Journal of Human Capital* **2**(2), 129–153.

Katz, L. F. and Murphy, K. M. (1992), 'Changes in Relative Wages, 1963-1987: Supply and Demand Factors', *Quarterly Journal of Economics* **107**(1), 35–76.

Kihlstrom, R. and Laffont, J.-J. (1979), 'A General Equilibrium Entrepreneurial Theory of Firm Formation Based on Risk Aversion', *Journal of Political Economy* **87**(4), 719–748.

King, R. G., Plosser, C. I. and Rebelo, S. T. (1988), 'Production, Growth and Business Cycles: I. The Basic Neoclassical Model', *Journal of Monetary Economics* **21**(2-3), 195–232.

Klapper, L., Laeven, L. and Rajan, R. (2006), 'Entry regulation as a barrier to entrepreneurship', *Journal of Financial Economics* **82**(3), 591–629.

Krusell, P., Ohanian, L. E., Rios-Rull, J.-V. and Violante, G. (2000), 'Capital-Skill Complementarity and Inequality: a Macroeconomic Analysis', *Econometrica* **68**(5), 1029–1053.

Lazear, E. P. (2004), 'Balanced Skills and Entrepreneurship', *American Economic Review Papers and Proceedings* **94**(2), 208–211.

Lazear, E. P. (2005), 'Entrepreneurship', *Journal of Labor Economics* **23**(4), 649–680.

Lloyd-Ellis, H. (1999), 'Endogenous technological change and wage inequality', *American Economic Review* **89**(1), 47–77.

Lloyd-Ellis, H. and Bernhardt, D. (2000), 'Enterprise, Inequality and Economic Development', *Review of Economic Studies* **67**(1).

Lucas, R. E. (1978), 'On the size distribution of business firms', *Bell Journal of Economics* **9**, 508–523.

Moscoso Boedo, H. J. and Mukoyama, T. (2010), 'Evaluating the Effects of Entry Regulations and Firing Costs on International Income Differences', *mimeo, U Virginia* .

Murphy, K. J. and Zabojnik, J. (2004), 'CEO pay and appointments: A market-based explanation for recent trends', *American Economic Review* **94**(2), 192–196.

Nugent, J. B. and Yhee, S.-J. (2002), 'Small and medium enterprises in Korea: Achievements, constraints and policy issues', *Small Business Economics* **18**(1), 85–119.

Piketty, T. and Saez, E. (2006), 'The Evolution of Top Incomes: a Historical and International Perspective', *American Economic Review* **96**(2), 200–205.

Poschke, M. (2010*a*), '"Entrepreneurs out of necessity": a snapshot', *IZA Discussion Paper* **4893**.

Poschke, M. (2010*b*), 'Who Becomes an Entrepreneur? Labor Market Prospects and Occupational Choice', *mimeo, McGill University* .

Poschke, M. (forthcoming), 'The regulation of entry and aggregate productivity', *The Economic Journal* .

Rajan, R. G. and Wulf, J. (2006), 'Are perks purely managerial excess?', *Journal of Financial Economics* **79**(1), 1–33.

Rauch, J. E. (1991), 'Modelling the informal sector formally', *Journal of Development Economics* **35**(1), 33–47.

Restuccia, D., Yang, D. and Zhu, X. (2008), 'Agriculture and Aggregate Productivity: A Quantitative Cross-Country Analysis', *Journal of Monetary Economics* **55**(2), 234–50.

Reynolds, P., Bosma, N., Autio, E., Hunt, S., De Bono, N., Servais, I., Lopez-Garcia, P. and Chin, N. (2005), 'Gobal Entrepreneurship Monitor: Data Collection Design and Implementation 1998-2003', *Small Business Economics* **24**, 205–231.

Romer, P. M. (1987), 'Growth based on increasing returns due to specialization', *American Economic Review* **77**(2), 56–62.

Rosen, S. (1982), 'Authority, Control, and the Distribution of Earnings', *Bell Journal of Economics* **13**(2), 311–323.

Samaniego, R. M. (2006), 'Industrial subsidies and technology adoption in general equilibrium', *Journal of Economic Dynamics and Control* **30**(9-10), 1589–1614.

Scopp, T. S. (2003), 'The Relationship Between the 1990 Census and Census 2000 Industry and Occupation Classification Systems', *U.S. Census Bureau Technical Paper* **65**.

Summers, R. and Heston, A. (1991), 'The Penn World Table (Mark 5): An Expanded Set of International Comparisons: 1950-1988', *Quarterly Journal of Economics* **56**, 327–368.

Terviö, M. (2008), 'The Difference that CEOs Make: An Assignment Model Approach', *American Economic Review* **98**(3), 642–668.

Teulings, C. (1995), 'The Wage Distribution in a Model of the Assignment of Skills to Jobs', *Journal of Political Economy* **103**(2), 280–315.

Tybout, J. R. (2000), 'Manufacturing Firms in Developing Countries: How Well Do They Do, and Why?', *Journal of Economic Literature* **38**(1), 11–44.

Urata, S. and Kawai, H. (2002), 'Technological progress by small and medium enterprises in Japan', *Small Business Economics* **18**(1), 53–67.

U.S. Department of Commerce (1975), *Historical Statistics of the United States: Colonial Times to 1970*, U.S. Government Printing Office, Washington, DC.

Vereshchagina, G. and Hopenhayn, H. (2009), 'Risk taking by entrepreneurs', *American Economic Review* **99**(5), 1808–1830.

Weir, D. R. (1992), A Century of U.S. Unemployment, 1890-1990, *in* R. L. Ransom, R. Sutch and S. B. Carter, eds, 'Research in Economic History', JAI Press, Greenwich, pp. 341–343.

Wiboonchutikula, P. (2002), 'Small and medium enterprises in Thailand: Recent trends', *Small Business Economics* **18**(1), 211–224.