Stars and Misfits
A Theory of Occupational Choice

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This version: August 2008

In some datasets, the self-employed earn markedly less than wage earners, even though those at the top end of the distribution earn more than their wage-earning peers. This observation is explained by a model of entrepreneurial choice that blends Lazear's [*Journal of Labor Economics*, vol. 23, pp. 649-680 (2005)] notion that entrepreneurs must be skilled in a variety of activities with the strong complementarity between skills central to Kremer's [*Quarterly Journal of Economics,* vol. 108, pp. 551-575 (1993)] O-ring theory of production. We test some predictions of the model using two datasets, which provide modest support for the model.

JEL Classification Codes: J24, L26.

Keywords: Entrepreneurship, self-employment, jack-of-all-trades, skill complementarity.

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Åstebro acknowledges financial support from the Social Sciences and Humanities Research Council and Natural Sciences and Engineering Research Council.

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Thompson gratefully acknowledges financial support from the Kauffman Professors Program of the Eugenio Pino and Family Global Entrepreneurship Center. Helpful comments from Alberto Galasso, Alan Carsrud, Brent Goldfarb, Jungmin Lee, Matt Mitchell, Ramana Nanda. and numerous seminar participants are much appreciated.

1. Introduction

This paper describes a model of occupational choice that blends Lazear's (2005) notion that entrepreneurs must be skilled in a variety of activities with the strong complementarity between skills central to Kremer's (1993) O-ring theory of production. The model is motivated by evidence on earnings of wage-earners and the self-employed. Figure 1, which replicates a figure from Hamilton's (2000) analysis of data from the 1984 Survey of Income and Program Participation (SIPP), plots the distribution of wage income and three measures of self-employment income. The distribution of earnings of the self-employed exhibits greater variance and is more skewed. For all three measures of self-employment income, median earnings of the self-employed were around 35 percent less than median wages, but by about the 75^{th} percentile the rank ordering was reversed. Hamilton's findings are echoed in other samples. Using data from the National Longitudinal Survey of Young Men (NLSY), Evans and Leighton (1989) also conclude that the self-employed earn less than wage earners. The samples used by Hamilton, and Evans and Leighton, are skewed toward low-income earners. Gort and Lee (2007) study earnings in the NSF Scientist and Engineers Statististical Data System (SESTAT), and find that average earnings for the self-employed exceed those for wage earners. Their sample, constructed from surveys of individuals with at least a Bachelor's degree in science or engineering, is

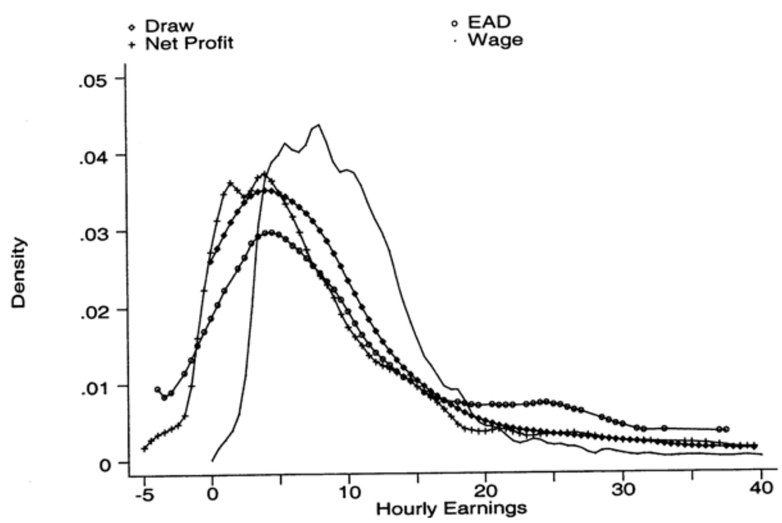

Fig 1. The density of earnings for wage earners and the self-employed. From Hamilton (2000, Figure 1).

skewed toward the upper end of the national earnings distribution where, if the patterns observed elsewhere hold generally, we expect self-employment earnings to be greater. Moreover, Gort and Lee still find that earnings among the lower percentiles of wage earners in their sample exceeds self-employment earnings at comparable percentiles.

We still seem to lack a theory of occupational choice that can make sense of this evidence. One candidate explanation is that Figure 1 simply reflects the greater uncertainty inherent in self-employment, and that occupational choice can be explained by a degree of risk aversion that makes everyone indifferent between wage employment and self-employment, or by variations in attitudes to risk that induces selection into self-employment by the least risk averse [cf. Kihlstrom and Laffont (1979)]. But evidence of a significant role for risk aversion is thin. First, the relationship between the mean and variance of earnings is too variable across samples to be consistent with a plausible degree of risk aversion.[1] Second, direct examinations of risk preferences fail to detect significant differences in the expected direction between wage earners and the self-employed [e.g. Brockhaus (1980), Masters and Meier (1988), Miner and Raju (2004), Sarasvathy, Simon and Lave (1998)].[2]

A second candidate explanation is that some individuals are forced into self-employment because unfavorable events limit wage-earning opportunities, while others are attracted into self-employment to pursue novel opportunities [see, for example, Block and Wagner (2006) and references therein]. The Global Entrepreneurship

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1. In Hamilton's sample, there is not even consistent evidence that the mean of self-employment income exceeds mean wage income: two of his three measures of self-employment yield a mean less than the average wage. Braguinsky and Ohyama (2007) study SESTAT data and find that, while the mean return to self-employment is strongly positive in skill-concentrated occupations, it is strongly negative in occupations that require only general skills. Rosen and Willen (2002) do establish a consistent mean-variance tradeoff in data from the Panel Study of Income Dynamics (PSID), but they conclude that the degree of risk aversion required to explain occupational choice exceeds conventional estimates by an order of magnitude. In stark contrast, Moskowitz and Vissing-Jørgensen (2002) wonder why entrepreneurial investors are willing to absorb such high risk with almost no gain in mean returns.

2. The distributions depicted in Figure 1 are of course not the conditional distributions faced by individuals; rather, they are the unconditional distributions that confound the risk faced by individuals with variation across individuals in expected returns. That is, the distributions in Figure 1 are not informative about the risk faced by entrepreneurs. However, the results in Hamilton (2000), and in Evans and Leighton (1989), are based on individual panel data sets.

Monitor [Reynolds *et al.* (2005)] has been especially keen in its data collection to distinguish between what they call 'necessity entrepreneurs' and 'opportunity entrepreneurs'. Necessity entrepreneurs are expected to have unusually low incomes while opportunities entrepreneurs are expected on average to report high incomes.[3]

Alternative explanations depend upon variations in ability. The upper end of the earnings distribution for the self-employed is populated by <u>stars</u> who earn more, sometimes much more [cf. Rosen (1981)], than wage earners at the same percentile. This view of selection into self-employment is consistent with the models of Lucas (1978), Calvo and Wellisz (1980), Evans and Jovanovic (1989), and Holmes and Schmitz (1990). The lower end of the distribution for the self-employed is populated by <u>misfits</u> who do not work well with others [e.g. Min (1984)], and they earn less than wage workers at the same percentile. These are simple ideas but, until recently, surprisingly few models attempt to explain in a single framework the disparate relative performance of the self-employed at both ends of the earnings spectrum.

In an early exception, MacDonald (1988) constructs a model in which the newly self-employed must learn over time about their abilities. His model predicts that the self-employed consist of a mix of high-ability experienced business owners and inexperienced, typically low-ability, agents, most of the latter of whom will eventually return to wage employment. However, MacDonald's story seems at odds with at least some of the evidence. Braguinsky and Ohyama (2007), for example, find that the returns to entrepreneurship are *higher* for the young. Hamilton (2000) notes that the theory cannot explain why many individuals persist for a long time in self-employment despite low earnings. Moreover, he observes, the earnings profile of the self-employed estimated from cross-sectional data (which of course confounds survivor bias with experience), never rises to exceed the alternative starting wage for an observationally equivalent wage earner. Hamilton exploits the two-year panel in his data to reveal an additional challenge for existing theories based on ability. He finds that the first-year income of wage earners who become self-employed in the second year is not significantly different from wage earners who do not switch, "except perhaps at the upper end" (p. 624). That is, he finds no evidence that on average low-ability workers select themselves into self-employment.

[3] More empirical work remains to explore these ideas. The GEM identifies the two types of entrepreneurs by asking respondents whether they started a business "to take advantage of a unique market opportunity . . . or because it was the best option available" [Reynolds *et. al* (2005)]. As the latter logically characterizes all decisions to enter self-employment, the question seems only to distinguish between innovative entrepreneurs and the self-employed.

The most progress made so far on developing a unified explanation for stars and misfits is by Ohyama (2007). He develops and tests a model in which variation in a unidimenisonal measure of ability determines occupational choice. Wages are linearly increasing in ability, while self-employment earnings may increase nonlinearly because self-employment earnings depend not only on ability, but also on the match between the requirements of the business and the education of the owner. In equilibrium, if self-employment earnings are strictly convex in ability, self-employment is chosen by the lowest- and highest-ability workers, with wage employment being the domain of those with moderate levels of ability.[4] Ohyama tests his model with data from the SESTAT, from which some intriguing supporting evidence is obtained.

The present paper also attempts to explain both the relatively high earnings of entrepreneurial stars and the low earnings of the self-employed elsewhere in the distribution with a model that relies only on variations in ability. Our framework is as follows. Production in each firm involves a number of distinct tasks, and output depends upon the skill with which each task is carried out. Abilities across tasks are complements in production. Firms may be organized in either of two ways. There are wage firms in which each task is carried out by a different specialist employee, and there are solo enterprises in which a single self-employed agent carries out all tasks himself. If an agent works for a wage firm, he will prefer to specialize in the task for which his ability is greatest. Consider now a potential match between an agent whose best task is, say, k, and a firm with a vacancy in k. The firm offers to hire the agent at a wage that depends positively on the agent's quality and negatively on the expected quality of substitute agents that could instead be hired. The agent responds to the offer by accepting it, launching his own startup and undertaking all activities himself, or continuing to search for wage employment. Complementarity of abilities across tasks has the following implications. If the agent's skill in task k is sufficiently lower than the average skill level in the rest of the firm, his value to the firm would be very low and may even be negative. As a result, the agent is offered an unacceptable wage, leaving him with the options of continued search or self-employment. If his skills across tasks are sufficiently balanced, he may prefer self-employment to continued search. Similarly, an agent whose skill level is sufficiently greater than the av-

4. See also Jovanovic (1994), which extends Lucas' (1978) span of control framework by allowing for a positive correlation between an individual's ability as a manager and as a wage employee. Jovanovic does not explicitly analyze any equilibrium in which both high- and low-ability agents manage firms, but this outcome can easily be obtained with appropriate assumptions about the relationship between managerial and employee abilities.

erage in the rest of the firm will be offered a wage less than he thinks he can obtain elsewhere. Again, if his skills across tasks are sufficiently balanced, he may prefer self-employment to continued search.

Section 2 describes the model in a static framework, where each agent faces a one-shot choice between wage-employment, self-employment, or unemployment. A number of outcomes are possible, and we analyze in some detail the most interesting one. The lowest-ability agents choose unemployment, agents with modest ability choose self-employment, agents with intermediate ability choose wage employment, and agents with high ability choose self-employment.[5] In this configuration of outcomes, the distribution of self-employment earnings exhibits more variance than wages regardless of the distribution of abilities. The model is also consistent with Lazear's (2005) contention that the self-employed on average have more balanced skills than wage workers.

The basic structure of the model is a simple blend of ideas from Lazear (2005) and Kremer (1993), but it is clearly also a close complement to Ohyama (2007). However, we have perhaps gone further than Ohyama in (i) developing an underlying technology that generates the required convexity of self-employment earnings, and (ii) exploiting implications of this technology for empirical analysis. There is also a (looser) complementarity with work on neccesity and opportunity entrepreneurs. Low-ability individuals have few attractive wage-earning opportunities and so may feel they were forced into self-employment; high-ability individuals, already doing quite well in wage employment, may well feel that they have been attracted into self-employment.

The distinction between the present model and the papers it complements becomes clearer in Section 3, which develops a dynamic model that allows for an explicit choice between self-employment and continued search for wage employment. Agents do not know their own abilities in different tasks until they have undertaken them either as a specialist or as a business-owner. When beginning wage-employment, they also do not know the abilities of agents they are about to work with. An agent engaged in wage search learns where his abilities stand relative to the rest of the population and may, upon learning that he is either much better or much worse than average, choose self-employment. Agents with abilities in either tail of the distribution are therefore likely to switch jobs frequently, and these are also agents who are likely to select self-employment. As a result, the dynamic model predicts

5. We explore how this configuration of outcomes changes as parameters change.

that individuals with varied employment histories are more likely to become entrepreneurs, which is consistent with a variety of empirical evidence [Wagner (2003, 2006), Lazear (2005), Åstebro and Thompson (2007)]. But the model contains a more distinctive prediction about the career histories of the self-employed at each end of the earnings distribution. The model predicts that individuals with low ability in most tasks will first try their luck in different job categories before concluding that they do not have a skill worth specializing in. Individuals with generally high ability will also be likely to change employers, but they are more likely to remain in the same job category as they search for a high-quality employer.

There is some indirect evidence for the ideas in the model. Elfenbaum, Hamilton, and Zenger (2008) find that in the SESTAT sample entrepreneurs are more likely to come from the upper and lower ends of the wage distribution, "consistent both with prior findings that misfits or low-ability 'slugs' enter self employment . . .and with selection-based models that suggest that most able workers become self-employed." [p.4]. Bruhn (2008) studies the effects of reforms facilitating new business registration in Mexico. Although the costs of registration declined markedly, few informal businesses were registered, leading Bruhn to conclude that informal businesses are largely owned by individuals with limited abiliy and limited aspirations. At the other end of the skill distribution, Groysberg, Nanda, and Prats (2007) have studied transitions into self-employment by financial analysts. They show that star analyists are more likely than others to become entreprneurs and, if they do, to be successful.

In Section 4 we add to this evidence by testing some implications of the model with two data sets: the Panel Study of Income Dynamics (PSID) and the Korean Labor and Income Panel Study (KLIPS). Consistent with Figure 1, self-employment earnings in both datasets are more variable than, but not on average higher than, wages. In both data sets, individuals who have a history of changing occupations earn less than those who do not change occupations. These findings accord with our model. However, varied work histories predict self-employment in only one of the samples studied.

Our model makes no unambiguous prediction about the earnings effect of changing employers but not occupation, but we included this test because a positive effect of employer variety on earnings would enable us to reject an alternative model, in which individuals choose self-employment because the numerous tasks that must be undertaken allow the self-employed to indulge a taste for variety [e.g., Åstebro and Thompson (2007)]. However, we find that switching employers is also associated with lower earnings. We conclude that our evidence on the effects of work history are equally consistent with the taste for variety model. However that model does not make any prediction about the greater variance of self-employment earnings that motivated the present study. It seems that the decision to enter self-employment is a complex one, driven by a diversity of motivations.

2. A Static Model

Let $\theta_j \in [0,1]$ denote the skill level applied to task j. Output in a wage firm is given by Kremer's (1993) O-ring production function, $y = An\prod_{j=1}^{n}\theta_j$. In this section, we consider the one-shot employment choice of a currently unemployed individual, i, with abilities θ_{ij}, $j = 1, 2, \ldots, n$. Following Lazear (2005), assume that if i specializes he will do so in the task for which his ability is greatest. Let this be task k, so that $\theta_{ik} \geq \theta_{ij}\ \forall j$. Individual i is matched with a single firm that has a vacancy in task k, the quality of which firm is indexed by $A\prod_{j\neq k}\theta_j$. He has the choice of joining the firm and specializing in task k, forming his own solo enterprise and undertaking all tasks himself, or remaining unemployed. Unemployment pays zero.

If the agent joins the wage firm, he is paid a wage that is increasing in his value to the firm, and decreasing in the value to the firm of searching for and selecting an alternative employee out of the general population. If the firm hires i, its output is $An\theta_{ik}\prod_{j\neq k}\theta_j$. If the firm chooses not to hire i, it can expect to produce $An\prod_{j\neq k}\theta_j\left[1-F(\underline{\theta})\right]^{-1}\int_{\underline{\theta}}^{1}\theta dF(\theta)$, where $F(\theta)$ is the distribution of ability in the population, and $\underline{\theta}$ is the lowest ability the firm is prepared to hire at a non-negative wage. Assume that (i) the value of searching for an alternative is equal to a proportion, $\beta < 1$, of the expected output, and (ii) if individual i is employed by the firm, he receives a constant fraction, α, of the difference between his value to the firm and the value to the firm of continued search. That is, i is offered a wage of

$$w_i(\theta_{ik}) = \alpha An\prod_{j\neq k}\theta_j\left[\theta_{ik} - \frac{\beta}{1-F(\underline{\theta})}\int_{\underline{\theta}}^{1}\theta dF(\theta)\right]. \tag{1}$$

Although the wage function is somewhat stylized, it is a convenient way to incorporate the key implication that high-quality firms pay a greater premium for quality than do low-quality firms (i.e., $w_i'(\theta_{ik})$ is increasing in $A\prod_{j\neq k}\theta_j$). A useful simplifying feature of (1) is that the ability level that yields a wage offer of zero, implicitly defined by

$$\underline{\theta} = \frac{\beta}{1-F(\underline{\theta})}\int_{\underline{\theta}}^{1}\theta dF(\theta), \tag{2}$$

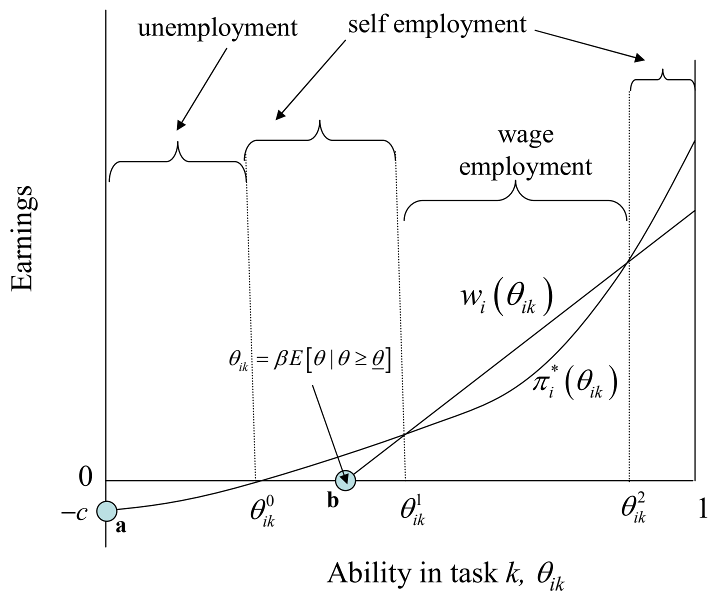

FIG 2. The choice between self-employment, wage employment, and unemployment, conditional on firm quality.

does not depend on firm quality.[6] This implication is not central to what follows but it allows for simple graphical analysis.

If i forms a solo enterprise, he receives $\pi_i = n\prod_{j=1}^{n}\theta_{ij} - c$, where c is a fixed cost of operating a firm. We shall assume throughout that $A > 1$, reflecting the fact that an agent with a given set of abilities is likely to be more productive in any task if he specializes in it.[7] We have in mind also that the particular value taken by α will be determined by the degree of friction in the labor market and the nature of bargaining between worker and firm. However, frictions are not modeled here so α is exogenous, and its value matters only in relation to the value of c. To reduce notation, therefore, we set α equal to unity.

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6. Assume $F(\theta)$ is a continuous function. Then the right hand side of (2) is continuous in $\underline{\theta}$, with a lower bound of $\beta E[\theta] > 0$. and (by l'Hôpital's rule) an upper bound of β. Hence there exists at least one fixed point. Moreover, as there are no mass points, $0 < \partial E[\theta \mid \theta \geq \underline{\theta}] / \partial \underline{\theta}$ <1 and the fixed point is unique. Intuitively, $\underline{\theta}$ is increasing in β . It also rises when ability in the general population rises.

7. An alternative interpretation is that established firms have learned over time how to be more productive with a given set of abilities.

Perfectly balanced skills. We begin with the special, and relatively simple, case in which individual i is identically-skilled in all tasks. We will inquire how the choices made by individual i depends on his skill level, the cost of operating a business, the quality of the potential employer, and the number of distinct tasks in the production technology. These questions are easy to answer by graphical means.

When individual i is equally skilled in all tasks, his earnings from self-employment are $\pi_i^*(\theta_{ik}) = n\theta_{ik}^n - c$.[8] Figure 2 plots this function along with the earnings from wage employment, $w_i\left(\theta_{ik}\right)$, for the most interesting case in which there are both high- and low-ability self-employed agents, wage earners and agents selecting unemployment.[9] The function $\pi_i^*\left(\theta_{ik}\right)$ is strictly convex, with $\pi_i^*\left(0\right) = -c$ and $\pi_i^*\left(1\right) = n - c$. The function $w_i\left(\theta_{ik}\right)$ is linearly increasing in θ_{ik}, beginning at zero when $\theta_{ik} = \beta E[\theta \mid \theta \geq \underline{\theta}]$. Its slope, $An\prod_{j \neq k}\theta_j$, is proportional to the quality of the firm. As long as the quality of the potential employer is neither too high nor too low, and the fixed cost not too high, there exists a range of abilities in task k, $\left[\theta_{ik}^1, \theta_{ik}^2\right]$, within which $w_i > \pi_i^*$ and outside of which $\pi_i^* > w_i$. Thus, an individual with balanced skills rejects wage employment if he is a star with high ability, but also if he is a misfit with low abilities in all tasks. Stars rejecting wage–employment always become self-employed. Misfits only become entrepreneurs if their ability exceeds $\theta_{ik}^0 < \theta_{ik}^1$. For those with the lowest ability, unemployment is the preferred option.

The effect of an increase in the fixed cost, c, of owning a firm is simply illustrated with the help of Figure 2. Raising c shifts $\pi_i^*\left(\theta_{ik}\right)$ down, which increases the extreme critical values, θ_{ik}^0 and θ_{ik}^2, while reducing the intermediate critical value, θ_{ik}^1. At the upper end of the quality distribution, an increase in c reduces the number of stars becoming self-employed, while raising their average quality. It also reduces the number of misfits who become self-employed, but it has an ambiguous effect on their average quality: the weakest misfits now choose unemployment, while some stars now choose wage employment. Overall, then, an increase in the cost of running a business has an ambiguous effect on the average quality of the self-employed, depending primarily on the distribution of ability levels. If costs rise sufficiently, the pools of stars and misfits may both vanish. Figure 3 summarizes how occupational choice varies

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8. The second subscript on θ is obviously not necessary to identify i's type. However, we retain it to highlight the fact that he is considering wage employment in which he will conduct task k.

9. This case requires that the parameters A, c, and β fall with certain ranges. Other cases will be discussed shortly.

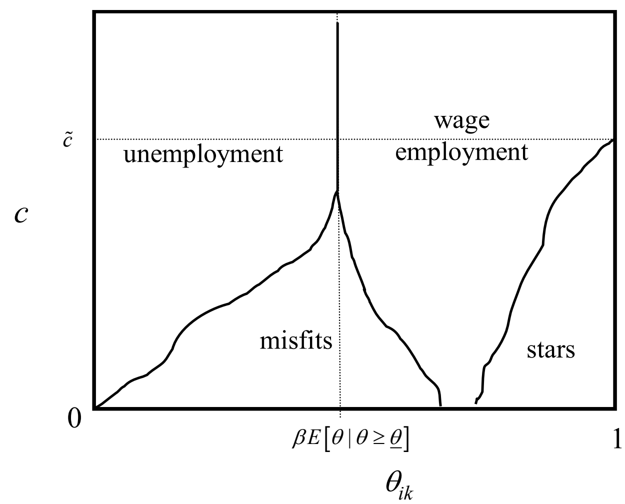


Fig 3. Occupational choice, by ability and the fixed cost of self-employment.

with the cost of running a business and with ability. When the fixed cost exceeds $\tilde{c}$, there is a simple separation between wage employment and unemployment, separated by $\theta_{ik} = \beta E[\theta \mid \theta \geq \underline{\theta}]$. The existence of individuals choosing self-employment requires a lower fixed cost. Figure 3 illustrates a case in which stars appear first as c falls, followed by misfits only after further declines in c. It is easy to produce numerical examples in which the reverse happens: from a point at which both misfits and stars are present, rises in the fixed cost of owning a business drive out stars first. A surprising possibility in this model, then, is that raising barriers to entry may lower the quality of startups.

Figure 3 also illustrates the case in which the quality of the potential employer is such that, even for arbitrarily low values of c, there are always some individuals that select wage employment. This need not always be the case. In Figure 2, a decline in the quality of the firm rotates the line $w_i\left(\theta_{ik}\right)$ clockwise around point **b**. The minimum ability that defines individual i as a star falls, while the maximum ability level for misfits rises. The effect in Figure 3 is to expand the areas accounted for by misfits and stars, without altering the area accounted for by the unemployed (see Figure 4).

For low values of c, sufficiently low-quality firms may be unable to recruit employees of *any* ability. If this happens, there is of course no longer any meaningful distinction between misfit and superstar entrepreneurs. When the quality of the potential employer rises, $w_i\left(\theta_{ik}\right)$ rotates counterclockwise around point **b**. Although the range of

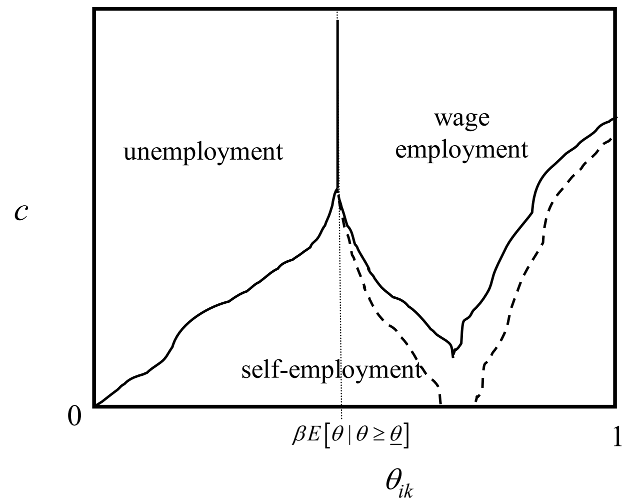


FIG 4. Declining firm quality reduces the area accounted for by wage earners, and expands the area accounted for by the self-employed. If firm quality declines sufficiently, stars and misfits may become connected sets.

abilities spanned by misfit entrepreneurs declines, an increase in the quality of wage employers can never drive them out entirely if they existed prior to the change in employer quality. But stars are readily driven out by a sufficiently large increase in employer quality, as Figures 5 and 6 illustrate. Somewhat surprisingly, then, an increase in incumbent firm quality drives out high-quality, but not low-quality, start-ups.

We have no clear results to report on the effect of a change in technology that increases the number of tasks that must be undertaken. In Figure 2, an increase in n may increase or decrease the slope of $w_i\left(\theta_{ik}\right)$. In the special case where the abilities of all incumbent employees are the same, the wage offered to a worker of any ability exceeding $\beta E[\theta \mid \theta \geq \underline{\theta}]$ rises if the quality of incumbent employees exceeds $e^{-1/n}$, and declines otherwise. Intuitively, the premium to ability is greater with more complex technology only if the incumbent employees are also sufficiently able to make good use of the technology. At the same time, the increase in n also affects $\pi_i^*\left(\theta_{ik}\right)$: it 'convexifies' the function while keeping its anchor at point **a** unaltered. For values of $\theta_{ik} < [>] e^{-1/n}$, $\pi_i^*\left(\theta_{ik}\right)$ is decreasing [increasing] in n, so increased complexity raises the productivity of the most able among the self-employed while it reduces that of the least able. So self-employment becomes less attractive for the less skilled and more attractive for the most able, while wage-employment may become more or less

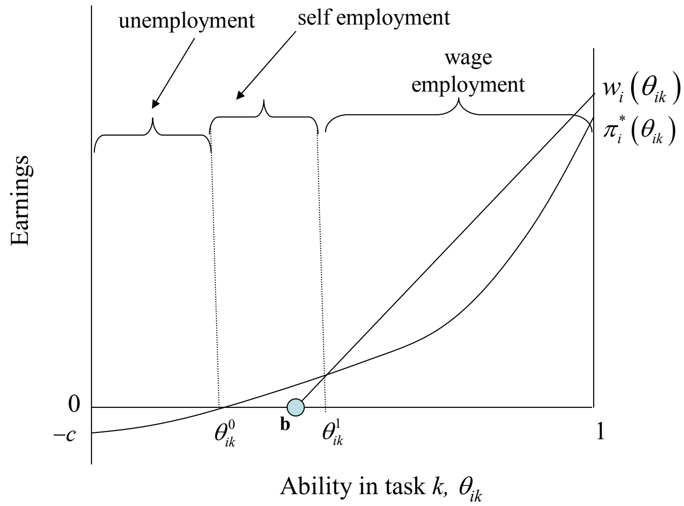


Fig 5. Rising incumbent quality drives only high-quality individuals out from self-employment. Compare with Figure 2.

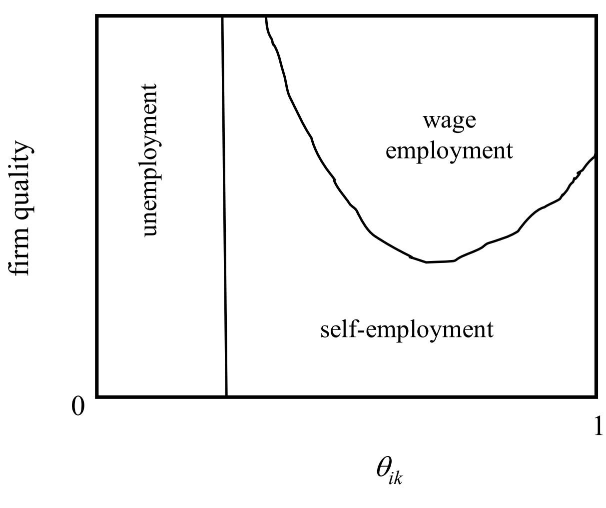


Fig 6. Occupational choice and the quality of the incumbent firm.

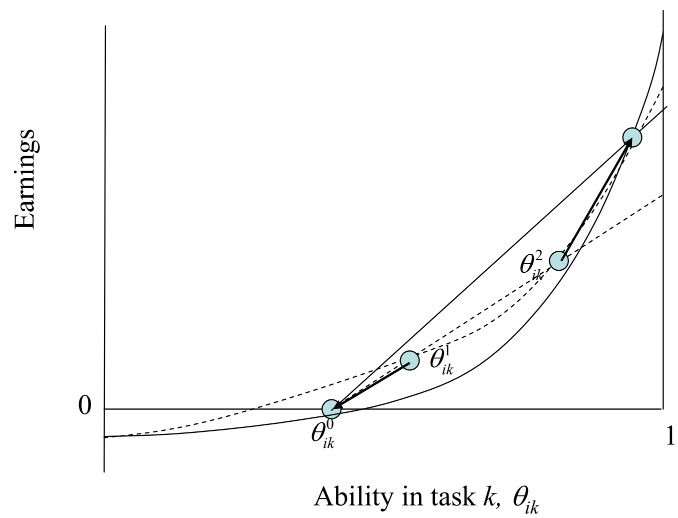


Fig 7. Increasing technological complexity has ambiguous effects, depending upon the initial configuration. The figure illustrates one outcome, starting from the configuration in Figure 2.

attractive for all abilities. The consequences of these changes in the functions for the values of θ_{ik}^1 and θ_{ik}^2, depend upon where the initial equilibrium lies; Figure 7 illustrates one of several possible outcomes.

We have so far assumed that unemployment pays zero.[10] Figure 8 illustrates the consequences of increasing the payoff to $b > 0$, which are intuitive: θ_{ik}^0 moves to the right, expanding the set of low-ability individuals who choose unemployment, and reducing the set of misfit self-employed. A sufficiently large increase in b may eliminate the category of self-employed misfits altogether.

Unbalanced skills. Assume that individual abilities are random draws from the unit interval, with joint distribution $G(\theta_1, \theta_2, \ldots, \theta_n)$, where G is strictly increasing in each argument. Consider now an individual with ability in task k of θ_{ik}. As this is his best skill, all other activities must be drawn from a conditional distribution with upper bound θ_{ik}. Let $s_i = \prod_{j \neq k} \theta_{ij}$ denote the product of his abilities in other tasks, and let $F_s(s \mid \theta_{ik})$ denote its distribution. Clearly, $F_s\left((\theta_{ik})^n \mid \theta_{ik}\right) = 1$. Assume that $F_s(s \mid \theta_{ik})$ is decreasing in θ_{ik}, which assumption holds for most underlying distributions of

10. This is to some extent just a convenient normalization. What matters for the choices of low-ability agents is the difference between the unemployment payoff and the cost, c, of opening a business.

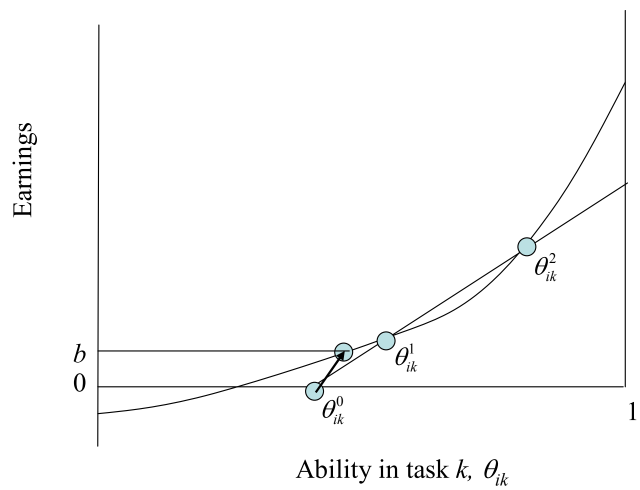


FIG 8. The effect of an increase in the payoff to unemployment.

task-specific abilities when an individual's abilities are uncorrelated or positively correlated across tasks. The conditional distribution of self-employment income, $\pi = n\theta_k s - c$, over individuals with ability θ_k is $F_\pi(\pi \mid \theta_k) = F_s\left((\pi + c) / (n\theta_k) \mid \theta_k\right)$, and $F_\pi(\pi \mid \theta_k)$ is also decreasing in θ_k. Let $\pi_\alpha(\theta_k)$ denote the level of self-employment income that satisfies $1 - F_\pi(\pi \mid \theta_{ik}) = \alpha$. That is, $\pi_\alpha(\theta_k)$, defines a family of iso-percentile lines. It is easy to verify that $\pi_\alpha(\theta_k)$ is increasing in θ_k and decreasing in α, that $\pi_0(\theta_k) = n\theta_k^n - c$, and that $\pi_1(\theta_k) = -c$.

Representative members of the family of iso-percentile lines are illustrated in Figure 9. The line $\pi_0(\theta_k)$ is, of course, exactly the same as the self-employment income line depicted in Figure 2. The intersection of $\pi_{0.1}(\theta_k)$ and $w(\theta_k)$ at point **a** can be interpreted as follows: among all individuals whose best skill level is θ_k^a and who are matched with a firm with quality indexed by the slope of $w(\theta_k)$, ten percent prefer self-employment and ninety percent prefer wage employment. Similarly, at point **b**, no one with ability θ_k^b prefers self-employment to wage employment. At point **c**, thirty percent of these individuals choose self-employment, while the remaining seventy percent choose unemployment.

Suitably extended to proportions, the comparative statics of the model are unchanged from the case of perfectly balanced skills. For example, an increase in the quality of the incumbent firm under consideration rotates $w(\theta_k)$ counterclockwise and reduces the fraction of individuals who prefer self-employment at every ability level θ_k. The proportion of stars who prefer self-employment falls to zero with a sufficient increase in incumbent quality, but there will always be some misfit entrepreneurs.

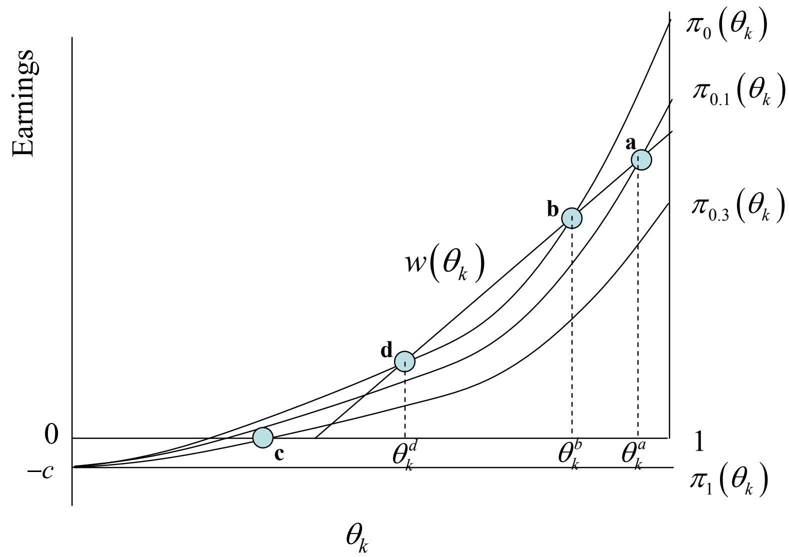
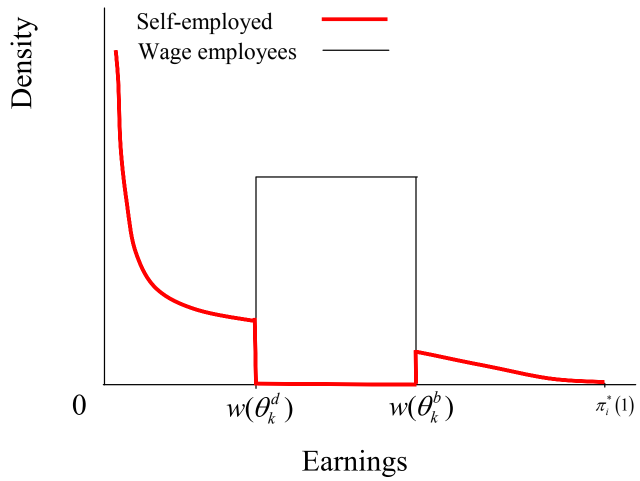


FIG 9. Occupational choice with unbalanced skills.

The distribution of earnings. Earnings distributions by employment type depend on the underlying distribution of abilities of unemployed agents and of firm qualities. We have been unable to produce a general analysis without resorting to numerical simulations. Hence, we restrict attention to the special case in which abilities across tasks are perfectly correlated, which at least enables us see the sort of possibilities that arise. We shall also assume that this ability is uniformly distributed on the unit interval.

We first condition on firm quality, beginning with the configuration in Figure 9. When abilities are perfectly correlated and θ_k is standard uniform, the fraction of agents who choose wage employment is $\theta_k^b - \theta_k^d$. Let $F(\pi)$ denote the distribution of *potential* self-employment earnings, which includes agents who do not actually choose self-employment. The fraction of agents choosing self-employment is therefore $\mu = 1 - (\theta_k^b - \theta_k^d) - F(0)$. As $\pi = n\theta_k^n - c$ is increasing in θ_k, the density of self-employment earnings among those who choose self-employment is readily obtained by the method of transformations:

$$\tilde{f}(\pi) = \begin{cases} \mu^{-1} n^{-(n+1)/n} (\pi + c)^{(n-1)/n}, & 0 \le \pi \le \pi(\theta_k^d) \vee \pi(\theta_k^b) \le \pi \le n - c \\ 0, & \text{otherwise} \end{cases}. \tag{3}$$



Equation (3) is plotted as the bold line in Figure 10. The light line is the distribution

Fig 10. Density of earnings by occupation conditional on the quality of the firm with which agents are matched. Each agent's skills are perfectly correlated across tasks.

of earnings for wage workers, which is uniform on the interval $[w(\theta_k^d), w(\theta_k^b)]$.

To obtain the unconditional earnings distributions, we need to sum each distribution conditioned on the quality of the potential employer over all incumbent firms. To do this we need the distribution of incumbent qualities, but this depends on the history of hires and separations in incumbent firms. One extreme assumption is that all incumbent employees are currently allocated to firms at random; in this case the term $\prod_{j\neq k}\theta_j$ has the uniform product distribution (which has an explicit formula) and the distribution of firm qualities $A\prod_{j\neq k}\theta_j$, is readily derived. At the other extreme, a firm consists of workers with identical abilities [this corresponds to the frictionless assignment equilibrium in Kremer (1993)]; then $\prod_{j\neq k}\theta_j = \theta^{n-1}$, the distribution of which is also readily derived when the underlying distribution of θ is uniform. The more appropriate assumption undoubtedly lies somewhere between these extremes, in which case the distribution of incumbent qualities cannot be written explicitly. However, we can make considerable progress, because the underlying distribution of *potential* self-employment income does not vary with firm quality. An increase in the quality of firms in Figure 10 reduces $w(\theta_k^d)$ while raising $w(\theta_k^b)$. As these two wages vary from firm to firm, the effect is to smooth out the sharp edges to the two density functions. How much smoothing takes place of course depends upon how variable

Fig 11. Density of earnings by occupation type, when agents' skills are perfectly correlated across tasks.

incumbent quality is. Figure 11 illustrates the general form of the unconditional distributions that arise.[11]

Figures 10 and 11 indicate that the mode for self-employment is at zero. However, this is an artifact of the assumption that θ_k is uniform. If instead the distribution of θ_k is bell shaped in the unit interval, the mode may well become interior. What does seem robust to a broad range of assumptions about abilities, however, is that the mode of self-employment earning is lower than the mode of wage earnings, and that its distribution is wider.

3. Employment Histories: A Dynamic Analysis

If an individual finds he has little aptitude for his current occupation, one might reasonably expect him to change occupation. Similarly, if an individual discovers he is unusually gifted in his current occupation, he may try to find a new employer able

11. Starting from the conditional distributions in Figure 10, less than perfect correlation between abilities also has a smoothing effect. Within the interval $[w(\theta_k^d), w(\theta_k^b)]$, there are still no agents who prefer self-employment, so the density of wages is horizontal between these two points. However, outside this interval, a fraction of agents choose self-employment, and the fraction doing so rises monotonically as we move further away from the interval.

and willing to properly reward him. In this section, we sketch a simple dynamic extention to the model that supports these conjectures and lays the basis for the empirical analysis to follow.

A.1 The model has two periods. At the beginning of the period 1, agent i is already engaged in wage-employment. In period 1, he may remain in the same job, switch to a new job, or begin self-employment. Self-employment is an irreversible choice. If he chose wage employment, he may remain in his current job in period 2 or begin self-employment.

A.2 $\boldsymbol{c}$**=0;** $\boldsymbol{b}$**=0:** There is no fixed cost to self-employment and unemployment pays zero. Hence, unemployment is never preferred to self-employment.

A.3 $\boldsymbol{n}$**=2;** $\boldsymbol{2\beta E[\theta|\theta>\underline{\theta}]=1}$**:** There are two tasks, a and b, and agent i is initally employed as a specialist in task a earning a wage $w(\theta_{ia},\theta_{jb}) = 2A\theta_{jb}(\theta_{ia} - \beta E[\theta \mid \theta \geq \underline{\theta}])$, where θ_{ia} is i's skill in task a, and θ_{jb} is the skill of the other employee in task b (i.e. the quality of the firm). To reduce notation, normalize the the value to the firm of continued search for a new employee to $2\beta E[\theta \mid \theta \geq \underline{\theta}] = 1$. Then, $w(\theta_{ia},\theta_{jb}) = A\theta_{jb}(2\theta_{ia} - 1)$.

A.4 Agent i knows his ability in task a, but he does not know his ability in task b. Let the conditional distribution be given by $F(\theta_{ib} \mid \theta_{ia})$. If i switches tasks he will immediately learn θ_{ib}.

A.5 The distribution of abilities in the population, $G(\theta)$, is the same for both tasks, and agent i knows this distribution.

Figure 12 summarizes the choices facing agent i. If i chooses to remain with his initial employer in period 1, he learns nothing about his ability in the other task or the distribution of firm qualities, so he will also choose to remain with his initial employer in the second period. Hence, this choice yields lifetime income of $v_{i1} = 2A\theta_{jb}(2\theta_{ia} - 1)$. If agent i chooses self-employment at the beginning of period 1, his expected lifetime earnings are $v_{i2} = 2\theta_{ia}\int_0^1 \theta_{ib} dF(\theta_{ib} \mid \theta_{ia})$. Agent i's third choice at the beginning of period 1 is to change jobs. He may switch employers but remain in the same task, in which case he earns $w_{ia}^1 = A\theta'_{jb}(2\theta_{ia} - 1)$ in period 1, where θ'_{jb} is the quality of his new employer. He may also switch task, in which case he earns $w_{ib}^1 = A\theta'_{ja}(2\theta_{ib} - 1)$ in period 1. At the beginning of period 2, i may reevaluate. He may either remain with his current job, earning $w_{ia}^2 = w_{ia}^1$ or $w_{ib}^2 = w_{ib}^1$, or he may move into self-employment.

Expected lifetime earnings from switching employers but remaining in the same task are given by

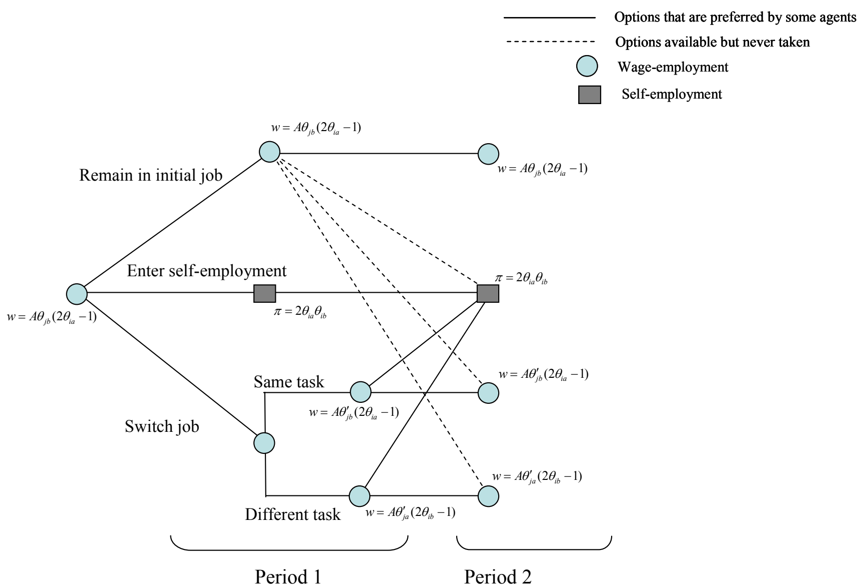


Fig 12. Employment choices in the dynamic model.

$$v_{i3} = \int_0^1 \Big(A\theta(2\theta_{ia} - 1)\Big) + \max\left\{\Big(A\theta(2\theta_{ia} - 1)\Big), \int_0^1 2\theta_{ia}\theta_{ib} dF(\theta_{ib} \mid \theta_{ia})\right\} dG(\theta) \ , \tag{4}$$

while switching tasks has an expected value of

$$v_{i4} = \int_0^1 \int_0^1 \Big(A\theta(2\theta_{ib} - 1) + \max\big\{A\theta(2\theta_{ib} - 1), 2\theta_{ia}\theta_{ib}\big\}\Big) dF(\theta_{ib} \mid \theta_{ia})\, dG(\theta) \, . \tag{5}$$

At the beginning of period 1, agent i's choice maximizes $v_{i\bullet}$.

Even though the model is simple and stylized, it does not yield unambiguous predictions. The choice that is made depends not only on i's ability in task a and the quality of his initial employer, but also on the premium to incumbency, A, the correlation between i's abilities, and the distribution of abilities in the population. For example, if A is sufficiently small, then wage employment will almost never be preferable to self-employment, which will be the dominant choice at the beginning of period 1. If A is sufficiently large, then high-ability individuals would never choose self-employment. Similarly, if abilities across tasks are perfectly correlated, then switching tasks as a wage earner is never optimal. The remainder of this discussion envisages an intermediate value of A, and uncorrelated abilities.

Consider extreme cases, and note that continuity of payoffs in ability ensure the same solution applies to agents "close" to the extremes. Consider first an individual with ability $\theta_{ia} < 1/2$. In period 1, he will either switch to task b or choose self-employment. He makes the decision by comparing v_{i2} and v_{i4}:

$$v_{i4} - v_{i2} = AE(\theta)\left[2E(\theta_{ib}) - 1\right] + \max\left[AE(\theta)(2E(\theta_{ib}) - 1) - 2\theta_{ia}E(\theta), 0\right]. \tag{6}$$

If abilities across tasks are negatively correlated, the agent may expect his ability on task b to exceed $1/2$, so that $2E(\theta_{ib}) - 1 > 0$ and $AE(\theta)(2E(\theta_{ib}) - 1) - 2\theta_{ia}E(\theta) > 0$. Therefore, $v_{i4} > v_{i2}$, and the agent chooses to switch tasks. Some agents will discover they are also no good at task b and move into self-employment in period 2. Others among them will discover they are quite good at task b but they ended up working for a low-quality firm; they also enter self-employment in period 2. In contrast, if abilities are sufficiently positively correlated, then $v_{i4} < v_{i2}$ and the agent chooses self-employment.

RESULT 1. *Agents with the lowest ability in task* a *switch task and employer, or enter self-employment when young. The worst paid wage workers in period 1 will become self-employed when old.*

At the other extreme, if $\theta_{ia} = 1$, there is no value to switching tasks. The agent thus compares the value v_{i1} of remaining with his current employer, with the value v_{i3} of carrying out the same task for a new employer, and the value v_{i2} of entering self-employment. If the quality of the initial employer is sufficiently high, then i remains with his current employer permanently. If the initial employer is low quality (i.e., if $\theta_{jb} < E(\theta)/2$), then i either switches employers or enters self-employment. If the agent does not expect his ability on task b to be especially high (i.e., he believes $2E(\theta_{ib}) < AE(\theta)$), he will choose to change employer in the first period. If $2E(\theta_{ib}) > AE(\theta) > 2A\theta_{jb}$, he will instead immediately switch to self-employment, because in this case $v_{i2} > v_{i1}$. In conclusion, the highest ability individuals face a number of different outcomes. They may remain with their first employer; they may switch to a new employer and remain there for two periods; they may switch to a new employer before entering self-employment; or they may switch immediately into self-employment. The last option is more likely with balanced skills. Nonetheless, it is possible to conclude the following:

RESULT 2. *Agents that enter self-employment after switching employers but not tasks are on average higher ability, and therefore earn more, than agents who enter self-employment after switching tasks.*

We can say more if we are willing to take a position on the value of A. A reasonable supposition is that (almost) all workers with the maximum ability in, say, task a would prefer working in a firm of quality $\theta_{jb} = 1$ to self-employment. This requires that $A>2$. Under this assumption, (almost) no high-ability individuals become self-employed without first changing employers. At the same time, individuals who proved to be sufficiently low-ability in their first specialized task and who become self-employed switch tasks (and hence employers) prior to establishing their own business. On balance, then, we expect the following in the data:

RESULT 3. *A variety of previous employers is predictive of eventual self-employment.*

4. Some Empirical Tests

In this section, we report results from some empirical tests of the model. We make use of two distinct data sets to relate work histories to earnings and to the likelihood of self-employment. The first is the Panel Study of Income Dynamics (PSID), a large but convenient sample in which respondents are asked to self-report variety of occupational history, and for which we are able to construct a measure of employer changes. The second is the Korean Labor and Income Panel Study (KLIPS), which shares many of the attractive features of the PSID; it contains somewhat better information about work histories and also contains a higher proportion of self-employed individuals. Some details of sample construction and variable definitions can be found in the Appendix.

For each dataset, we first check that earnings of the self-employed do indeed exhibit greater variation than wages. We then assess how work histories influence earnings. The dynamic model predicts that a history of changing occupations (i.e. changing the type of job held) is associated with lower earnings, while changing employers without changing occupations has an ambiguous effect with earnings. Finally, we assess how work histories influence the likelihood of becoming self-employed. The dynamic model predicts that variety in either employers or occupations raises the probability of self-employment.

Are these predictions distinct from those of alternative models relating variety in work histories to earnings and self-employment? One such alternative is Lazear's (2005) interpretation of occupation-switching as a way to accumulate skill in preparation for self-employment. In contrast to the present model, skill accumulation associates occupational variety with greater earnings. This we will easily be able to test. A second alternative is that individuals change employers and occupations because of a taste for variety [e.g., Ghiselli (1974), Hamilton (2000), Judge, Heller, and Mount

(2002), Hyytinen and Ilmakunnas (2004), Åstebro and Thompson (2007)]. Taste for variety unambiguously associates employer variety with lower earnings, while our model admits relationships of either sign. This distinction will be harder to test: if the data reveal a positive relationship we may reject the taste for variety specification in favor of our model, but a negative relationship is not discriminating.

4.1 The Panel Study of Income Dynamics

Our PSID sample contains 37,122 observations on 8,113 individuals who were household heads active in the labor force at the time they were interviewed. The interview dates included in the sample span 1981 to 1990. Of these 8,113 individuals, fifteen percent were self-employed at some point during their appearance in the sample. However, only seven percent of the observations record self-employment. Thus, individuals recording self-employment at some point during their appearance in the sample were wage earners for a little over half of the time on average. Seventy-three percent of the sample was male, and 34 percent had a college degree. At the time of entry into our sample, 63 percent of the sample was younger than 35, 21 percent was older than 45, and 9 percent older than 55. Twenty-seven percent of the sample worked in manufacturing when they first entered the sample, 20 percent in wholesale and retail businesses, and 18 percent in professional services (including business, educational and health services).

We begin by comparing earnings of wage earners and the self-employed. Figure 13 plots the distributions of annual labor income of household heads for wage-earners and for the self-employed, while columns (1) and (2) of Table 1 provides some summary statistics. The earning distributions in the PSID mimic the SIPP data reported by Hamilton (2000) and summarized in Figure 1. Mean earnings are similar among wage-earners and the self-employed, while median earnings are markedly lower for the self-employed. The variance of earnings is much larger for the self-employed; their incomes are lower at the 25^{th} percentile and higher at the 95^{th} percentile; at the 99^{th} percentile, self-employment labor income is about 50 percent greater than the labor income of wage-earners.

These differences in incomes are not simply a result of easily observable composition effects. The same patterns are evident in columns (3) and (4) of Table 1 and in Figure 14, which summarize the distributions of the unexplained earnings obtained from the residuals of a regression of log income on gender, age, education, and industry, occupation, and year dummies. As with the raw data, the median and lower percentiles of the distribution are smaller for the self-employed than for wage earners, while

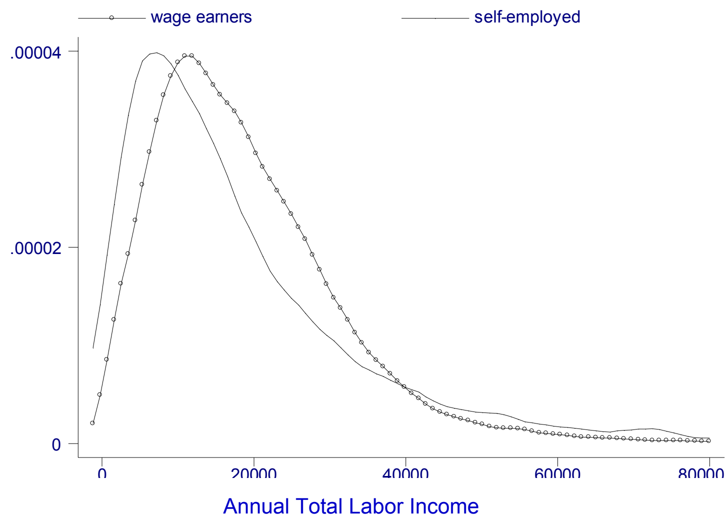


FIG 13. Distribution of income for wage-earners and the self-employed; PSID sample.

TABLE 1
Distributions of income; PSID Sample

	TOTAL INCOME		RESIDUAL INCOME*	
	WAGE EARNERS	SELF-EMPLOYED	WAGE EARNERS	SELF-EMPLOYED
	(1)	(2)	(3)	(4)
Mean	19,223	20,295	.023	−.276
Std. Dev.	13,910	24,445	.647	.953
25^{th} percentile	10,040	6,984	−.247	−.770
50^{th} percentile	16,671	13,791	.107	−.187
75^{th} percentile	25,302	25,092	.417	.329
95^{th} percentile	41,975	57,637	.858	1.098
99^{th} percentile	65,034	125,000	1.219	1.741
Observations	35,137	2,872	35,137	2,872

* Summary statistics for residuals from a regression of ln(income) on observables (gender, age, a dummy for college education, and industry, occupation, and year dummies)

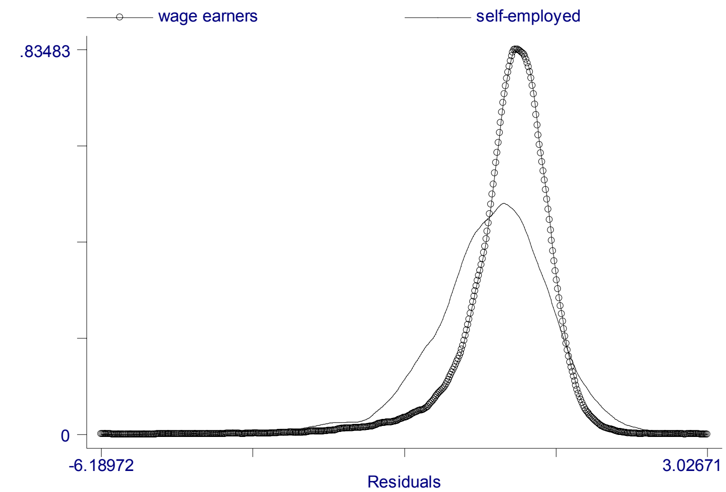


Fig 14. Distribution of residual labor income for wage-earners and the self-employed; PSID sample.

the upper percentiles are larger. In addition, the mean of the residuals is smaller for the self-employed. The magnitudes of differences in residual income between the two groups are economically significant. On average, wage workers earn 2.3 percent more than is predicted by observables, while the self-employed on average earn almost 27 percent *less* than we would predict from observables. At the 25$^{\text{th}}$ percentile, a self-employed person earns less than one third his predicted income, while a wage earner at the same percentile earns three-quarters his predicted wage. Differences of similar magnitudes, but in favor of the self-employed, can be observed at the upper percentiles.

We constructed two characterizations of employment history from the PSID data. The first is a binary indicator of changes in job types. The PSID asks respondents whether they have "had a number of different kinds of jobs, or have . . mostly worked in the same occupation." We constructed a binary variable, OCC. CHANGE, set equal to one if the response indicates a career spanning a variety of occupations, and zero otherwise. The second variable, AV # EMPLOYERS, measures the observed fraction of times interviewed that an individual stated he had been with his present employer less than twelve months. The PSID variable # MOS THIS EMP records how long an individual had worked for his present employer. A value less than twelve implies at least one change of employer in the previous year. We created for each observation a dummy variable equal to one if # MOS THIS EMP was less than twelve. For each year an individual is in our sample, we recorded in AV # EMPLOYERS the average value of these dummy variables taken over all previous interviews.

Table 2 reports summary statistics for our two measures of variety in individual work histories. As measured by OCC. CHANGE, 58 percent of the responses report stability in the type of job held. The proportion is higher among women (67 percent versus 55 percent), but there are no marked differences across age groups. In contrast, there is no difference between men and women in AV # EMPLOYERS, but there are marked differences across age groups. We are much more likely to have detected no changes in the annualized number of employers for older respondents: about eighty percent of those over age 45 and only sixty percent of those under 35 report AV # EMPLOYERS equal to zero. This is consistent with the familiar observation that older workers exhibit greater employer stability (although this is often referred to as job stability). Overall, AV # EMPLOYERS equals zero in 68 percent of observations. Detectable changes of employer occur less frequently than once every three years (AV # EMPLOYERS < 0.3) for 85 percent of the sample, and less frequently than once every 1.67 years (AV # EMPLOYERS < 0.6) for 98 percent.

TABLE 2
Observed Work Histories, 1981-1990 (fraction of observations);
PSID Sample

	OCC. CHANGE		AV # EMPLOYERS			
	0	1	0	(0, 0.3]	(0.3, 0.6]	>0.6
TOTAL	0.58	0.42	0.68	0.17	0.14	0.02
Male	0.55	0.45	0.68	0.17	0.15	0.02
Female	0.67	0.33	0.67	0.16	0.13	0.02
Age [17-35)	0.57	0.43	0.61	0.17	0.19	0.03
[35-44]	0.55	0.45	0.69	0.20	0.10	0.01
[45-54]	0.61	0.39	0.78	0.15	0.07	0.01
>=55	0.61	0.39	0.84	0.12	0.04	0.00
OBS.	38,009		34,599			

To explore the effect of employment variety on earnings, we begin by comparing earnings by OCC. CHANGE. Columns (1) and (2) of Table 3 provide the summary statistics for the raw data, showing that mean and median earnings are indeed lower for responses indicating a variety of previous occupations. In fact, consistent with the model, earnings for OCC. CHANGE = 1 are lower at each reported percentile. Composition effects might matter, but the direction in which these effects work are not *a priori* clear. Young people are more likely to try different occupations in any given length of time, but older people have had more time on which to work in different occupations. On the other hand, younger people are more likely to respond to the survey question "have you had a number of different kinds of jobs" with their entire career in mind, while older workers may disregard their early work history. Consequently, we adjust earnings for observables as before and report, in columns (3) and (4) and in Figure 15, residual earnings by OCC. CHANGE. The results match those from the raw data. Mean residual earnings are markedly lower for observations with OCC. CHANGE = 1, as are the earnings for this group at each percentile. At the sample means of each group, individuals reporting a stable occupational history earned 3.2 percent more than could be predicted from observables, while individuals reporting a varied history earned 4.4 percent less.

TABLE 3

Distributions of income by occupational variety; PSID Sample

	TOTAL INCOME		RESIDUAL INCOME*	
	OCC. CHANGE=0	OCC. CHANGE=1	OCC. CHANGE=0	OCC. CHANGE=1
	(1)	(2)	(3)	(4)
Mean	19,727	18,729	.032	−.044
Std. Dev.	15,404	14,339	.672	.688
25^{th} percentile	9,901	9,683	−.247	−.328
50^{th} percentile	16,725	16,129	.128	.043
75^{th} percentile	25,907	24,503	.440	.372
95^{th} percentile	44,708	40,493	.883	.858
99^{th} percentile	71,155	65,089	1.283	1.243
Observations	21,921	16,088	21,921	16,088

* Summary statistics for residuals from a regression of ln(income) on observables (gender, age, a dummy for college education, and industry, occupation, and year dummies)

To separate the effects of employer-switching from task-switching, we attempt to condition on individuals who have not changed occupation by restricting the sample to responses with OCC. CHANGE = 0. Table 4 reports raw earnings data and residual earnings for responses with AV # EMPLOYERS above and below the mean. After con-

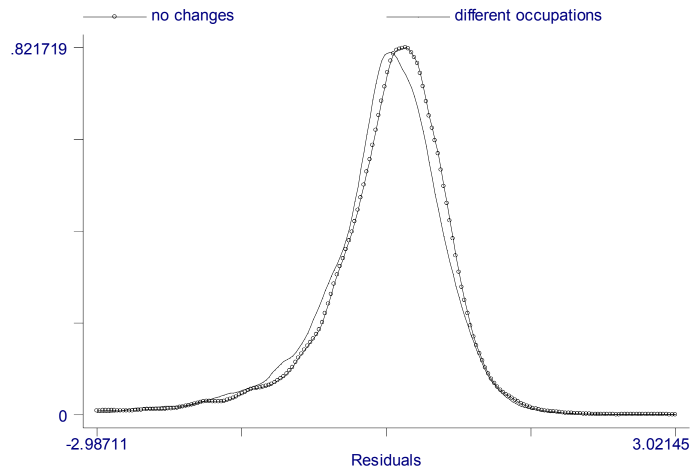


FIG 15. Distribution of residual labor income by OCC CHANGE; PSID sample.

ditioning on OCC. CHANGE = 0, respondents with a greater tendency to change employers report lower incomes at each point in the distribution. Our model does not exclude these results, but they are explicitly supportive of the taste for variety model. There is, however, a confounding problem. OCC. CHANGE is likely to be a rough measure of occupational variety, and it is correlated with changes in employer. As a result, conditioning the sample on OCC. CHANGE = 0 may not fully accomplish what we are after in Table 4. The model suggests that AV # EMPLOYERS matters only for those at the upper end of the skill distribution. We recalculated Table 4 after restricting the sample to the college educated, and again after restricting the sample to skill-intensive occupation classes (computer specialists, engineers, managers, and administrators). The results are unchanged. For the college educated, mean incomes are $27,335 for individuals with AV # EMPLOYERS below the mean and $24,076 for the remainder. The corresponding means for the skill-occupation subsample are $31,813 and $28,303, respectively.

In Tables 3 and 4, our analysis of earnings are limited to comparisons across types of the raw distribution of earnings and the distribution of residual earnings after partialing out the contribution of a number of observable individual characteristics. One might suppose that we could exploit the panel data to incorporate, at least, fixed effects, and perhaps even individual effects that have different impacts on earnings for wage-earners and the self-employed [e.g., Lemieux (1998), Suri (2008)]. Doing so, however, would lead us to address a rather different question than the one we are concerned with. Our analysis is directly concerned with the effect of unobserved ability on earnings distributions; fixed effects estimations yield estimates of the distributions of wages and self-employment earnings that would prevail if people were assigned at random to one of the two groups.[12] Indeed, it is not even obvious to us that the residual earnings distributions are more informative than the raw data, because observables such as age may matter in part because they proxy for ability.

TABLE 4

Distributions of income by occupational variety; PSID Sample

	TOTAL INCOME		RESIDUAL INCOME*	
AV # EMPLOYERS:	BELOW MEAN	ABOVE MEAN	BELOW MEAN	ABOVE MEAN
	(1)	(2)	(3)	(4)
Mean	20,651	18,058	.018	−.011
Std. Dev.	15,546	15,744	.689	.651
25th percentile	10,415	9,124	−.246	−.306
50th percentile	17,746	14,995	.120	.065
75th percentile	27,289	22,823	.433	.390
95th percentile	46,185	41,316	.879	.827
99th percentile	74,181	68,860	1.262	1.273
Observations	14,105	5,858	14,105	5,858

* Summary statistics for residuals from a regression of ln(income) on observables (gender, age, a dummy for college education, and industry, occupation, and year dummies)

Table 5 considers the effect of work history on the probability of becoming self-employed. We ran logit regressions, with the dependent variable, Y_{it}, equal to one if individual i was self-employed in year t and zero otherwise. The sample is restricted to observations in which $Y_{i,t-1} = 0$, so that $Y_{it} = 1$ indicates a switch into self-employment sometime during the previous twelve months (rather than survival in self-employment over the previous twelve months). Columns (1) through (4) report the results of logit regressions. Column (5) reports the results of a conditional logit with individual fixed effects. The conditional logit forces us to exclude MALE and OCC. CHANGE, both of which are (almost)

12. For example, Lemieux (1998) is concerned with the effects that working in a union job has on wages, and therefore needs to control for unobserved individual effects that simultaneously affect the wages earned and the choice to take a union job.

constant for each individual, and it drops all individuals who never become self-employed or who were always self-employed (about ninety percent of the sample). The results across all columns are consistent: OCC. CHANGE is not significantly associated with the probability of becoming self-employed, but AV # EMPLOYERS is. Wage earners who have been observed switching employers frequently are more likely to become self-employed, and this effect remains significant even after controlling for individual fixed effects.

TABLE 5

Probability of Becoming Self-Employed; PSID Sample

	DEP VAR =1 IF SELF-EMPLOYED IN CURRENT YEAR, 0 OTHERWISE				
	LOGIT REGRESSIONS				CONDITIONAL LOGIT
	(1)	(2)	(3)	(4)	(5)
LAGGED LN(INCOME)	**−0.33**	**−0.25**	**−0.24**	**−0.24**	**0.40**
	(−5.9)	**(−4.2)**	**(−4.2)**	**(−4.2)**	**(3.0)**
COLLEGE EDUCATED = 1	−0.08	−0.11	−0.11	−0.11	−0.30
	(−0.8)	(−1.1)	(−1.1)	(−1.1)	(−0.7)
MALE = 1	**0.59**	**0.58**	**0.57**	**0.57**	———
	(4.6)	**(4.6)**	**(4.5)**	**(4.5)**	
AGE (YEARS)	−0.00	0.00	0.00	0.00	−0.04
	(−1.2)	(0.1)	(0.1)	(0.1)	(−0.20)
OCC. CHANGE = 1	0.07	———	0.04	0.03	———
	(0.9)		(0.51)	(0.3)	
AV # EMPLOYERS	———	**1.07**	**1.06**	**1.02**	**1.46**
		(5.2)	**(5.1)**	**(3.7)**	**(2.4)**
(OCC_CHANGE = 1) X	———	———	———	0.09	———
(AV # EMPLOYERS)				(0.2)	
AV. LOG LIKELIHOOD	−0.11	−0.11	−0.11	−0.11	−0.29
PSEUDO $R2$	.08	.08	.08	.08	.09
OBSERVATIONS	28,947	25,947	25,947	25,947	2,428

Sample restricted to all observations in which the respondent was a wage worker in the previous year. All regressions include dummies indicating industry and occupation during the previous year, as well as year dummies. Z-scores in parentheses; entries in **bold** significant at the five percent level.

It might be of interest to note the change in the sign of the coefficient on lagged income between the logit and conditional logit regressions. The logit regressions suggest that unexpectedly low income drives people into self-employment, consistent with the notion that many self-employed individuals become so by necessity. However, controlling for individual fixed effects yields a positive association between previous income and entry into self-employment. Assuming wealth and income are positively correlated in this sample (as in others), the conditional logit suggests that (i) low-ability induces entry into self-employment, but (ii) there are liquidity constraints limiting entry [e.g. Evans and Jovanovic (1989)].

4.3 Korean Labor and Income Panel Study

This subsection reports findings from 4,151 observations on household heads from the 1998 cross section of the KLIPS.[13] About 25 percent of the respondents are self-employed, much more than the seven percent recorded in the PSID. The sample is 63 percent male; 37 percent is younger than 35, thirty percent is older than 45, and ten percent is older than 55. As in the previous subsection, we begin by comparing incomes of wage earners and the self-employed. Figure 16 plots the distributions, while Table 6 provides summary statistics. The previous subsection reported findings using annual earnings, although adjusting for time spent working to obtain hourly earnings produced similar results. Our conclusions are also much the same in the KLIPS sample whether we report monthly or hourly earnings. Somewhat arbitrarily, we report the latter here. The relative earnings of wage workers and the self-employed are similar to patterns already observed in the SIPP and the PSID: mean earnings of the self-employed are somewhat higher than for wage earners; self-employed earnings are much lower at the lower percentiles, and much higher at the upper percentiles, of the income distributions. Yet again, these differences are not easily explained by composition effects; as columns (3) and (4) of Table 6 show, the earnings disparities survive adjustment for observables including gender, age, education, industry and occupation.

We characterize the occupational history of our cross-section of individuals in two ways. In the first, the KLIPS survey asks respondents how many jobs they have worked in. In the second, respondents are asked about their previous occupations. As in the PSID, the survey is attempting to distinguish between individuals who have

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13. The KLIPS is a panel data set with many features similar to the PSID. The first observations were collected for 1998. The sample in that year consisted of 13,317 adults aged fifteen or older in 5,000 households living in seven metropolitan and urban areas.

TABLE 6

Distributions of 1998 hourly earnings; KLIPS Sample

	TOTAL HOURLY EARNINGS		RESIDUAL HOURLY EARNINGS*	
	WAGE EARNERS	SELF-EMPLOYED	WAGE EARNERS	SELF-EMPLOYED
	(1)	(2)	(3)	(4)
Mean	0.66	0.78	−.056	.130
Std. Dev.	0.446	1.47	.367	1.408
25^{th} percentile	0.36	0.27	−.250	−.317
50^{th} percentile	0.56	0.48	−.079	−.115
75^{th} percentile	0.85	0.83	.097	.195
95^{th} percentile	1.46	2.08	.462	1.401
99^{th} percentile	2.19	5.68	1.175	4.241
Observations	2,276	975	2,276	975

* Summary statistics for residuals from a regression of hourly earnings on gender, age, a dummy for college education, industry dummies, and occupation dummies).

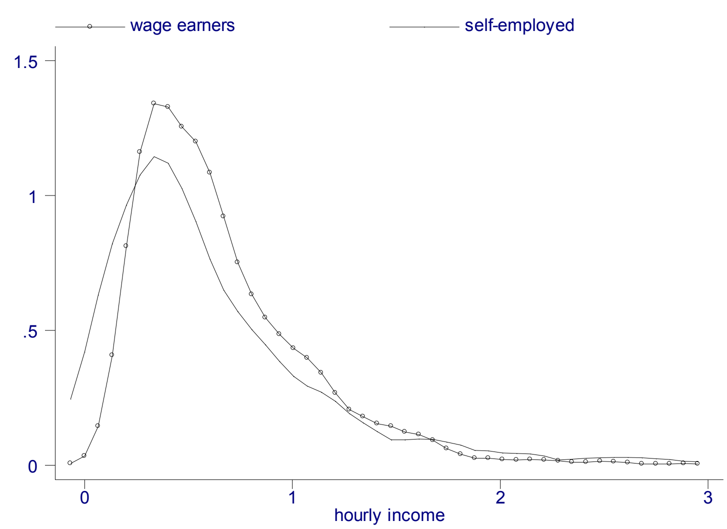

FIG 16. Distribution of hourly earnings for wage-earners and the self-employed; KLIPS sample.

changed employer while essentially being engaged in the same task, and those who have also changed tasks. Figure 17 and Table 7 compare the distribution of earnings among respondents indicating they have not changed occupations at all with the distribution of those that have switched occupations, and the distribution of earnings for those that have and have not changed jobs.

The raw distributions by occupation change provide some modest support for the model. While there is no difference in mean earnings for individuals with a history of changing occupations and those without, the earnings of the former group are lower at the 25th, 50th and 75th and 95th percentiles; the lack of difference in means is explained by a small number of high income self-employed above the 95th percentile. As in the PSID, individuals with a history of changing employers also have lower earnings than those who do not. One might reasonably anticipate two confounding problems already raised with the PSID. The first is that age is correlated with the numbers of occupation and employer changes. The second is that most individuals changing occupations must in practice do so by changing employers. To address these confounding factors, Table 8 summarizes the distributions of earnings after adjusting for age and the square of age. It also compares distributions by employer change only for individuals with no occupation changes. The adjustments have no effect on the results.

Table 7

Hourly Earnings by Occupation and Job Change: KLIPS Sample

	Occupation Change		Job Change	
	No Change	Different Occs.	No Change	Different Jobs
Mean	.672	.684	.729	.676
Std. Dev.	.723	1.379	.641	1.015
25th percentile	.325	.298	.364	.312
50th percentile	.521	.474	.588	.500
75th percentile	.806	.739	.937	.781
95th percentile	1.591	1.563	1.590	1.582
99th percentile	3.125	3.750	2.976	3.125
Observations	1,249	730	1,271	1,980

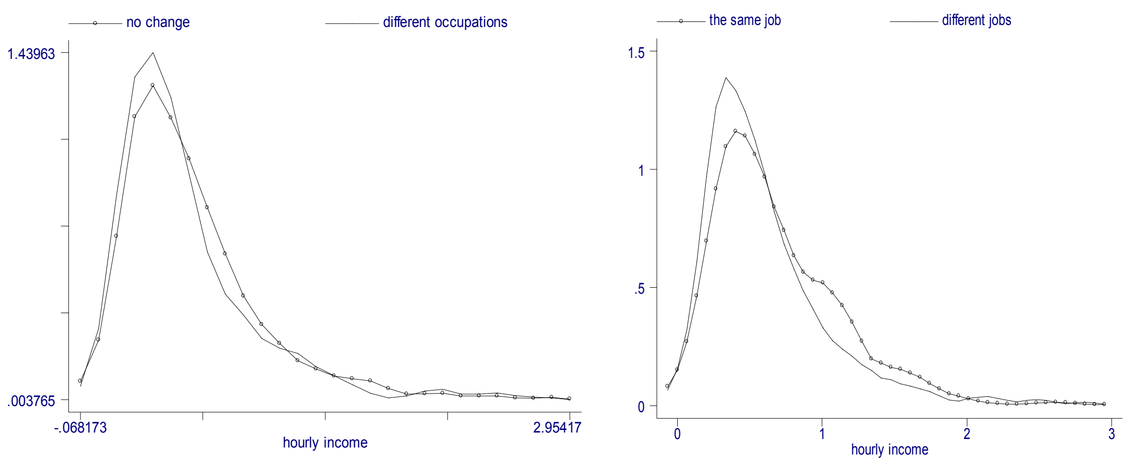

Fig 17. Distribution of hourly earnings by occupation changes (left panel) and job changes (right panel); KLIPS sample.

Table 8

Age-Adjusted Hourly Earnings by Occupation and Job Change: KLIPS Sample

	Occupation Change		Job Change (Individuals with No Occ. Change)	
	No Change	Different Occs.	No Change	Different Jobs
Mean	−.036	−.037	.056	−.036
Std. Dev.	.716	1.374	.621	1.009
25th percentile	−.363	−.429	−.238	−.387
50th percentile	−.143	−.225	−.037	−.177
75th percentile	.082	.017	.229	.065
95th percentile	.864	.859	.888	.863
99th percentile	2.324	2.944	2.181	2.347
Observations	1,249	730	1,271	1,980

Table 9

Probability of Becoming Self-Employed (KLIPS Sample).

	Dep Var =1 if self-employed in current year, 0 otherwise					
	All	College educated	No College	All	College educated	No College
	(1)	(2)	(3)	(4)	(5)	(6)
Age (years)	**0.045**	**0.035**	**0.042**	**0.031**	**0.045**	**0.027**
	(12.7)	**(4.46)**	**(10.2)**	**(6.25)**	**(3.98)**	**(4.74)**
Male	0.071	−0.118	**0.277**	**0.551**	0.003	**0.761**
	(0.85)	(−0.67)	**(2.81)**	**(4.49)**	(0.01)	**(5.25)**
No. of previous occupations	**0.174**	**0.473**	0.051	0.041	−0.108	0.048
	(2.2)	**(2.7)**	(0.56)	(0.44)	(−0.44)	(0.45)
No. of previous jobs	−0.059	−0.089	−0.070	−0.091	−0.150	−0.091
	(−1.13)	(−0.77)	(−1.19)	(−1.71)	(−1.24)	(−1.52)
Industry dummies	No	No	No	Yes	Yes	Yes
Av. Log Likelihood	−0.54	−0.43	−0.58	−0.57	−0.50	−0.58
Pseudo $R2$	.05	.03	.04	.04	.05	.04
Observations	3,619	1,299	2,320	2,050	595	1,453

Sample restricted to observations in which the respondent was a wage worker in the previous year. Z-scores in parentheses; entries in **bold** significant at five percent level.

Finally, Table 9 reports logit regressions estimating the impact of work history on the probability of becoming self-employed. Column (1) shows that occupational variety is positively associated with the probability of self-employment, while employer variety has no statistically significant effect. However, the remaining columns, which add indicators for the industry of occupation in the previous year, reveal that even this singular impact is driven by industry composition effects among the college-educated. These conclusions are unchanged if, as we did for the PSID, we add lagged income or a dummy variable for college education to the pooled sample.

5. Conclusions

In Hamilton's (2000) study of earnings patterns among wage earners and the self-employed in the SIPP, self-employment earnings exhibit greater variation than wage earnings, but do not offer higher average earnings in compensation. The same patterns can be found in data from the NLSY [Evans and Leighton (1989)] and the SESTAT [Gort and Lee (2007)], as well as the PSID and the KLIPS (this paper). In this paper, we rationalize these observations with a model combining features of Lazear's (2005) multi-task theory of entrepreneurship and the complementarity of task abilities from Kremer's (1993) O-ring theory of production.

In addition to predicting earnings distributions consistent with the motivating evidence, our model also predicts testable relationships between work histories, the odds of becoming self-employed, and earnings. First, individuals with a history of changing occupations earn less than those specializing in one occupation. Second, histories of changing occupations and histories of changing employers within the same occupation class are both associated with greater odds of becoming self-employed. We tested these predictions using two datasets. We found that (i) in both datasets earnings of the self-employed exhibit greater variation than earnings of wage workers; (ii) in both data sets, individuals who have a history of changing occupations earn less than those who do not change occupations; and (iii) in one of the samples, varied work histories raise the odds of self-employment. These results are reasonably consistent with our model.

Because our model is specifically about how (unobserved) ability induces observable behaviors, we are less concerned about controlling for ability than is customary in work on occupational choice. However, the tests of our model are likely confounded with unobserved variations in atttitudes twoward self-employment. As Hamilton (2000) and others have previously noted, many individuals enter into self-employment in part for non-pecuniary reasons. One such reason is that some individuals have a taste for variety in their work experiences, which induces some individuals to choose wage work in different occupations or with different employers before undertaking the varied activities demanded by running a business. To test our model against taste for variety, we also explored the earnings effect of having a history of changing employers but not occupation. Our model makes no clear prediction on this score, but a positive effect would imply rejection of taste for variety. In both datasets, however, we found a ngeative effect. However, the taste for variety model does not make any prediction about the greater variance of self-employment earnings that motivated the present study.

Appendix

A.1 PSID Sample and Variable Construction

Our initial sample from the PSID, containing 37,401 individuals, consists of eleven sub samples for each year from 1980-1990. We make use of fourteen primary variables from the PSID: 1968 INTERVIEW NUMBER, PERSON NUMBER, SEQUENCE NUMBER, RELATIONSHIP TO HEAD, AGE (HEAD), SEX (HEAD), EMPLMT STATUS (HEAD), EDUCATION(HEAD), 3-DIGIT MAIN OCCUPATION (HEAD), 3-DIGIT MAIN INDUSTRY (HEAD), NUMBER OF DIFFERENT JOBS (HEAD), SELF-EMPLOYMENT/OTR (HEAD), MOS-THIS EMP (HEAD), and TOTAL LABOR INCOME (HEAD).

The combination of 1968 INTERVIEW NUMBER and PERSON NUMBER creates a unique identifier for each individual. SEQUENCE NUMBER indicates whether or not an individual was in the family at the time of the interview, while RELATIONSHIP TO HEAD describes an individual's relationship to the household head.[14] Employment data in the PSID only apply to household heads, so we use these two variables to ensure that all the individuals in the sample were current household heads in the interview year. As this study focuses on the comparison of the self-employed and wage earners, the sample was further limited to individuals who were either working (EMPLMT STATUS (HEAD)=1) or temporarily laid off (EMPLMT STATUS (HEAD)=2). Observations with EMPLMT STATUS (HEAD) not equal to 1 or 2 were removed from the sample. Restricting the sample in this way left 13,072 individuals.

(1) COLLEGE. The value of EDUCATION (HEAD) ranges from 0 (cannot read) to 8 (college and advanced or professional degree). Observations with EDUCATION (HEAD) coded with 0 (cannot read) or 9 (not available) are excluded. For the remaining observations, we created a dummy variable, COLLEGE, and set it to one if EDUCATION (HEAD) was coded with 6 (college but no degree), 7 (BA, but no advanced degree, or 8 (advanced or professional degree)

(2) SEM. The PSID variable SELF-EMPLOYMENT/OTR (HEAD) is coded as 1 (someone else employs respondent), 2 (both someone else and self), 3 (self only), 9 (NA/don't know), or 0 (Inappropriate; unemployed; and permanently disabled, retired, housewife, and student). Observations with codes equal to 9 or 0 are removed from the sample. For the remaining observations, we created a dummy variable, SEM, and set it to one if SELF-

[14] It is coded as 10 (1 for 1981 and 1982) if an individual was the household head at the time of the previous or current interview.

EMPLOYMENT/OTR (HEAD) is coded with 2 or 3 (it makes little difference to our results if we code 1 and 2 together instead of 2 and 3). We also created the variable LSEM, which simply records the value of SEM from the previous interview.

(3) OCCUPATIONAL CHANGE. The PSID variable NUMBER OF DIFFERENT JOBS (HEAD) is a crude indicator for the frequency with which an individual changes occupation type. The PSID asks, "Have you had a number of different kinds of jobs, or have you mostly worked in the same occupation you started in, or what?" The permissible answers (beyond 'don't know' or 'never worked', which we eliminate from the sample) are:

> "1. Have had a number of different kinds of jobs; mentions more than two kinds of jobs (changes in both).
>
> "3. Both; have had a number of different kinds of jobs but mostly the same occupation; mentions two kinds of jobs (changes of jobs, but not occupations)
>
> "5. Mostly the same occupation; same job all of working life."

To construct an indicator for individuals who frequently work in different activities, we construct a binary variable, OCCUPATIONAL CHANGE, which we set equal to 1 if the answer was coded as 1, and zero if the answer was coded as 3 or 5.

(4) PREVIOUS EMPLOYERS. The PSID variable MOS THE EMPLOYER reports how long an individual had worked for his present employer. A value less than twelve implies at least one change of employer in the past year. We created for each observation a dummy variable equal to one if MOS THE EMPLOYER was less than twelve. For each year an individual is in our sample, we recorded in PREVIOUS EMPLOYERS the average value of these dummy variables taken over all previous interviews.

(5) INCOME. This variable is equal to the PSID variable, TOTAL LABOR INCOME (HEAD). It is the summation of a household head's labor part of farm income; labor part of business income; wages income; bonuses, overtime, and commissions; income from professional practice or trade; labor part of market gardening income; and labor part of income from roomers and boarders. Nominal income in the PSID was converted to constant 1982 dollars using the CPI.

(6) *Industry and Occupation Dummies.* Using the PSID variable 3-DIGIT MAIN INDUSTRY (HEAD), Dummy variables were constructed to indicate employment in thirteen industries (agriculture, forestry, and fishery; mining; construction; manufacturing; transportation and warehousing; information; utilities; wholesale and retail trade; finance, insurance, and real estate; professional, business, education, and health services; entertainment and rec-

reation; other services including repair, personal services, membership association; and public administration). Individuals employed in agriculture forestry, and fishery were excluded from the analysis. Since public administration is characterized by low rates of self-employment, this profession was also dropped from the analysis. Similarly, we created dummy variables from the PSID variable 3-DIGIT MAIN OCCUPATION (HEAD) to indicate employment in nine distinct occupations (computer specialists and engineers; professional and kindred workers; managers and administrators; sales workers, clerical, and kindred workers; craftsman and kindred workers; operatives, laborers, and farmers; and service and private household workers). Observations with undefined industry or occupation were also removed from the sample.

A.2 KLIPS Sample and Variable Construction

The data come from Korean Labor and Income Panel Study (KLIPS). We only focus on the first interview wave (1998). In the first wave, respondents were classified into three categories (wage earners, non-wage earners, and unemployed workers) and were interviewed with separate questionnaires. Our original sample consists of 13,321 individuals. After removing those who: (1) were younger than 18 [781]; (2) were unemployed [6,119] or unpaid family workers [529] at the time of being interviewed; (3) were engaged in agriculture, forestry, or fisheries [362], an undefined industry [262], the armed forces or an undefined occupation [479]; (4) were, in the previous job, engaged in agriculture, forestry, or fishery [130], an undefined industry [149], the armed forces, or an undefined occupation [316]; (5) were unpaid family workers previously [43]. We are left with 4,151 individuals who were above 17, worked either as wage earners or self-employed workers in the previous job and were currently employed in 1998.

<u>Primary Variables</u>

The primary variables we select from the raw data can be classified into two categories: demographic variables and employment variables. The three demographic variables include: age, gender, education. As wage workers and self-employed workers were interviewed with different questionnaires, the dataset provides two sets of employment variables: one is for wage workers and the other is for self-employed workers. Variables contained in both sets include current industry, industry of previous job, current occupation, occupation of previous job, the monthly average wage, regular/irregular working hours for a week, the wage in the previous job, the order of the current job in the job history, and previous job status (1=regular wage worker, 2=irregular wage worker, 3=employer with employees, 4=self-employed without employees, and 5=unpaid family worker), prior work experience (up to ten jobs and occupations).

Generated Variables

Industry (*indy*1). The variable *indy*1 records thirteen industries: mining; manufacturing; tility; construction; wholesale and retail; hotels and restaurants; transportation and communication; financial institution and insurance; real estate, renting, and leasing; public administration; education; health and social work; and other community, repair, and personal service, respectively.

Occupation (*ocp*1). The variable *ocp*1 indicate nine categories of occupation: legislators, senior officials and managers; professionals; technicians and associate professionals; clerks; service and sales workers; skilled agricultural workers; craft and related trade workers; plant, machine operators, and assemblers; and elementary occupations, respectively.

Hourly Income (*hinc*1). Obtained by dividing monthly income by four times weekly average working hours.

First Job or Not (*firstj*1). In KLIPS, the respondents were asked whether their current job was their first job. The variable, *firstj*1, is one if the answer is yes, and two otherwise.

Number of previous jobs (*jn*1). If the current job was not the person's first job, he was further asked whether it was the 3rd, the 4th job, and so on up to ten. Variable *jn*1 is generated by subtracting one from this number.

Number of different previous occupations (*nvals*). The variable *nvals* is constructed by counting the number of different occupation codes recorded in the respondents' previous ten jobs, if there are any.

Dummy variable for occupation change (*above*). If a respondent never changed his occupational field in the past jobs, variable *nvals* would be equal to one. Thus, a dummy variable recording occupation change (*above*) is generated. It equals 0 if *nvals* equals one, and 1 if *nvals* is greater than one.

Dummy variable for self-employment (*sem*1). If the survey type records that the person was interviewed with the questionnaire for unpaid workers, it implies in our dataset that he was self-employed at the time of interview. Thus, the variable, *sem*1, equals one. Otherwise, it equals zero.

Dummy variable of previous self-employment (*lag_ sem*1). If a respondent's previous job status was employer with employees or self-employed without employees, we consider both of these cases as self-employment and *lag_ sem*1 is recorded as 1. Otherwise, *lag_ sem*1 equals 0.

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