The Rewards for Entrepreneurial Ability to Adopt and Implement Advanced Technologies*

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Abstract

Theoretical studies of entrepreneurship have developed a number of insightful theories to examine active roles played by entrepreneurs. On the other hand, recent empirical studies tend to find a negative self-employment premium. Several versions of non-monetary compensation hypotheses have been proposed to rationalize this finding and our attention is now shifting to characteristics of entrepreneurs who are willing to sacrifice monetary earnings in exchange for non–monetary benefits such as "being one's own boss." This paper revisits a traditional question of what entrepreneurs do to earn economic rewards and tries to offer a unified theoretical and empirical analysis of entrepreneurs who get rewarded for performing productive entrepreneurial functions. The empirical analysis of this study systematically examines a broad range of information on highly-educated scientists and engineers contained in Scientists and Engineers Statistical Data System (SESTAT). The overall analysis suggests that highly educated self-employed are rewarded for capability of absorbing and implementing advanced technical knowledge.

Key Words: Entrepreneurship, Post Secondary Education, Earnings differentials, Human capital

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1 Introduction

What do entrepreneurs do to earn economic rewards? In an attempt to answer this question, traditional economic studies on entrepreneurship have developed a number of insightful theories of entrepreneurship. Joseph Schumpeter (1934) characterized entrepreneurs as an economic agent who earns economic rents by performing innovation. In Frank Knight's view (1921), entrepreneurs are residual claimants and entrepreneurial rewards are associated with perception of uncertainty. Not limited to their work, most theoretical discussions were centered on active roles played by entrepreneurs in productive activities.

Such heroic entrepreneurs however seem elusive in recent applied work of entrepreneurship that examines a large body of data by empirically identifying entrepreneurs with independent business owners. Hamilton (2000), for example, concludes from his finding of a negative entrepreneurship premium that "Overall, it appears that many workers are willing to enter and remain in self-employment despite receiving returns substantially below their alternative paid employment wage." This view is not at odd in the recent empirical literature, but it rather seems to reflect a tentative consensus among economists since other recent empirical studies in similar spirit reached qualitatively the same conclusion (e.g. Blanchflower and Oswald, 1998, Moskowitz and Vissing-Jørgensen, 2002, Åstebro and Thompson, 2007). Naturally, these empirical studies help to direct our attention to characteristics of entrepreneurs who are willing to sacrifice monetary earnings in exchange for non–monetary benefits such as "being one's own boss" or "preference for a variety of tasks."

This paper revisits the traditional question of what entrepreneurs do for economic values and tries to offer a unified theoretical and empirical analysis of entrepreneurs who get rewarded for performing productive entrepreneurial functions. More specifically, building on Calvo and Wellisz's idea (1980), we theoretically characterize entrepreneurial activities as learning, adopting and implementing advanced technical knowledge. In today's world where the nature of production technology is increasingly sophisticated, technical progress is one of the important channels for the creation of profitable opportunities, and entrepreneurs may actually get rewarded for their capability of absorbing and applying new general knowledge to firm-specific purposes. In our empirical study, we follow the common practice in applied work of entrepreneurship by identifying entrepreneurs with self–employed (i.e. independent business owners). This empirical strategy is mainly to avoid some potential controversy arising from ad hoc empirical identifications of entrepreneurs and, more importantly, is to make our empirical findings comparable with those in recent empirical studies. A notable difference of self–employed in our sample from those in previous studies is that our self–employed are highly educated in the sense that all of them have completed post–secondary education. Of course, higher education itself does not a priori favor self–employed or paid employees in terms of earnings capacity. In fact, the formal model of this paper shows that it is a purely empirical question.

The basic building blocks of the model come from Jovanovic (2006) who analyzes asymmetric business cycles caused by technical inefficiency associated with adoption of technology. As in his model, entrepreneurs make a decision on adoption of an advanced technology, and uncertainty surrounding the advanced technology requires costly adjustment of their skill–mix for its appropriate implementation. The model in this paper assumes that the cost of filling a given technical gap between the ideal skill–mix and their actual skill–mix decreases with a degree of expertise in their job or more generally a level of human capital. Entrepreneurs with high human capital can effectively mitigate potential adverse effects arising from adoption of the advanced technology on its implementation. Superior entrepreneurial ability in turn encourages them to choose a more advanced technology, whereas entrepreneur's inability to deal with uncertainty about the advanced technology make them stick to an outdated technology. As a consequence, entrepreneurial earnings increase on average with a level of human capital. As Schultz (1980) emphasizes, this type of reward is not the same as simply collecting windfalls and bearing losses, although technical adoption entails risk. It is a reward earned by their entrepreneurial performance.

The idea of entrepreneurial ability to hit or come closer to the ideal skill–mix is not new and essentially corresponds to the concept of "allocative ability" introduced by Welch (1970). In his seminal work, allocative ability is referred to as worker's ability to acquire and decode information about costs and productive characteristics of other inputs, and to redirect scarce resources within the organization in response to changes in economic conditions. The concept of allocative ability appears to have attracted economist's renewed attention in the debate on the cause of the rise in wage inequality between skilled and unskilled workers. Greenwood and Yorukoglu (1997), for instance, propose the technology–skill complementarity or skill–biased technical change hypothesis by arguing that "Setting up, and operating, new technologies often involves acquiring and processing new information. Skill facilitates this adoption process." In their argument, differences in allocative ability are translated into earnings differentials between skilled (more educated) and unskilled (less educated) workers. In our model, this ability is crucial for determining earnings differential between entrepreneurs and non–entrepreneurs as well as within entrepreneurs.

The model in this paper also predicts two different sorting patterns into the entrepreneurial sector: "pooling" and "separating" sorting patterns. When human capital is relatively unimportant in adoption and implementation of an advanced technology, individuals with low human capital select to be entrepreneurs and individuals with high human capital becomes paid workers. This sorting pattern is called a pooling sorting pattern. On the other hand, a separating sorting pattern emerges when human capital is relatively more valued in entrepreneurship. Under the separating sorting pattern, individuals become paid employees when their human capital is moderate, whereas there are two types of entrepreneurs: high human capital and low human capital entrepreneurs. In other words, "heroic" and "desperate" entrepreneurs coexist under the separating sorting pattern. The former type of entrepreneurs possesses an exceptionally high capacity and produces the good by using advanced technologies while the latter type of entrepreneurs does not have capability to deal with advanced technologies and ends up with sticking to out–of–date technologies.

Our data come from the restricted-use of Scientists and Engineers Statistical Data System (SESTAT) developed by the National Science Foundation (NSF). SESTAT is a large and rich data set on scientists and engineers who have completed post–secondary education in the United States. All individuals in our sample thus have at least bachelor's degree in science or engineering fields. The self-employed part of SESTAT data set may not be representative of an average small business owner in the United States, but an empirical examination of the highly–educated workforce in the science and engineering fields is indispensable for the main purpose of this study because we believe that such highly–educated self–employed are more likely to engage in job activities closely relating to adoption and implementation of advanced technologies than educationally disadvantaged self–employed. The systematic empirical examination of self-employed in SESTAT therefore is more appropriate than analyzing self-employed in general population surveys.

We test implications of the theoretical model against our data and examine whether our empirical findings can be explained better by our model or non–monetary compensation hypothesis. A key research variable in our empirical study is education–job–relation variable (EJR). Respondents to NSF surveys were asked about the relationship between the current job and the highest educational degree they have earned (with three choices, closely related, somewhat related, and not related at all). This EJR variable is used in our analysis to measure the importance of one's expertise in the current job. Because of mainly data limitations, past studies have not been unable to systematically examine how earnings of self-employed or those of paid workers are affected by the fact that their formal education is closely related to their jobs. This is therefore considered to be a new element of this study.

Our empirical study reveals that one's expertise in job or more generally human capital has larger impacts on self–employment earnings than on paid wages. According to our estimates, for example, self–employed whose job is closely related to their doctorate education earn approximately 31 percent more than self–employed whose job is not related to their doctorate education. The corresponding earnings differential for paid employees is only 4.1 percent. Not limited to this example, our estimation indicates that one's human capital acquired through formal education is valued more in entrepreneurship. The importance of human capital in entrepreneurship is also translated into earnings differentials between self–employed and paid employees. Our estimation shows that the entrepreneurship premium –earnings of self–employed relative to earnings of paid employees– is positive at several locations of the earnings distribution for self–employed whose jobs are closely related to their highest educational degree. On the other hand, the entrepreneurship premium is estimated to be negative for self–employed whose jobs are not related to their highest educational degree. Thus, the former type of self–employed receive pecuniary returns from self–employment activities whereas the latter type of self–employed suffer earnings losses. These findings are consistent with the prediction of our model under the separating sorting pattern. In other words, we find heroic and desperate entrepreneurs in our sample. It is worthwhile to mention that these interesting findings would not be obtained if we did not disaggregate self–employed into two categories according to a degree of expertise in one's job.

We also employ a counterfactual setting to investigate whether an individual's decision on the employment status is primarily made based on pecuniary returns or on non–pecuniary benefits. Our estimation results from a structural probit model confirm that a monetary differential is a major determinant of an individual's entry decision into the self–employment sector. This fares better with our model rather than the non–monetary hypothesis. The evidence with regard to the earnings differential under the counterfactual is mixed. Our data will support the non–monetary hypothesis if the estimated earnings differential for a person randomly chosen from the target population is negative. We do not find this evidence for individuals who hold jobs closely related to their education, but we find it for individuals who are working outside their educational fields. Our overall analysis suggests that our model can explain behaviors of highly educated self–employed in our sample, especially high capacity self–employed, better than the non–monetary compensation hypothesis.

The rest of the paper is organized as follows. In section 2 we construct a theoretical model to study a source of entrepreneurial rewards and an individual's choice of employment status. We also derive testable empirical implications from the model. Section 3 presents empirical results. Section 4 concludes.

2 The Model

We begin our theoretical analysis with a simple static model where the main entrepreneurial functions are to adopt and implement advanced technologies. The basic building blocks of the simple static model come from Jovanovic (2006) who analyzes asymmetric business cycles caused by unpredictable skill demand resulting from adoption of technology. The simple model presented below departs from his model by explicitly including an element that individuals are heterogeneous with respect to human capital they posses, and it focuses on examining implications of such heterogeneity for an individual's employment status choice between entrepreneurs and paid employees. The model is also designed to analyze within and between earnings differentials of these two groups arising from a sorting pattern. This section abstracts a process of individual's human capital accumulation and we therefore take a distribution of human capital as given.

2.1 The Setup

All individuals are assumed to have identical preferences over a composite consumption good, c, and their preferences are specified by

$$E\left(\ln c\right) \tag{1}$$

where E indicates a mathematical operation of expectation. Although individuals have identical preferences, they are heterogeneous with respect to a level of human capital they posses. Accordingly, their earning capacity varies to reflect this heterogeneity. Let θ denote a level of one's human capital and G denote a distribution function of θ with a bounded support $\left[0, \overline{\theta}\right]$. Since the term "human capital" has been used to mean many different things in the human capital literature, further elaboration of the term would help clarify some results from theoretical and empirical analyses of this study. In this study a level of one's human capital is synonymous with a degree of one's expertise in his or her job.

To purchase the consumption good, individuals earn labor income by becoming either a paid worker or an entrepreneur. When individuals select to be paid workers, they inelastically supply their labor services to the labor market and earn paid wage, y^p, given by

$$y^p = \exp\left(w\theta\right) \tag{2}$$

where w is a wage rate per the efficiency unit of labor. Thus, paid employees are able to earn high income when they have considerable expertise in their job.

On the other hand, when an individual decides to be an entrepreneur, he produces a homogeneous good by employing a production technology characterized by (A, s_A) and sells his output at the price, normalized to unity, in the product market. More specifically, an entrepreneur has an access to the following production technology:

$$\widetilde{y} = \exp\left\{A - \frac{1}{2}(s_A - h)^2\right\} \tag{3}$$

where A is the level of technology, h is his skill–mix, and s_A is the skill–mix ideal for technology A.

Entrepreneurs can adopt and implement an advanced technology in order to increase their output. Adoption of an advanced technology is assumed to be costless, but uncertainty surrounding the new technology requires adjustment of his skill–mix for its appropriate implementation. Formally, the initial level of his technology A can be augmented by choosing any amount $x \geq 0$ at free of charge, so that a new level of his technology, A', becomes

$$A' = A + x \tag{4}$$

We make use of the "non–recall" assumption that the entrepreneur is unable to return to the old technology A once he chose the new level of his technology A'.

Adoption of the new technology A' however causes unpredictable demands on the skill–mix. In particular, the skill–mix ideal for the new technology A' changes stochastically according to

$$s_{A'} = s_A + x\epsilon \tag{5}$$

where $\epsilon \sim F$ is an i.i.d. random variable with mean zero and variance σ^2. Note that, for given h, his potential log output, $\ln \widetilde{y}'$, after adopting technology level A' is given by

$$\begin{aligned} \ln \widetilde{y}' &= A' - \frac{1}{2}(s_{A'} - h)^2 \\ &= \ln \widetilde{y} + x - (s_A - h)\, x\epsilon - \frac{1}{2}(x\epsilon)^2 \end{aligned}$$

Adoption of an advanced technology increases his output in general (i.e. when ϵ is set equal to 0), but it entails a risk of decreasing his output due to a technical inefficiency. Adoption of an advanced technology therefore may end up with a reduction in his output if the skill–mix ideal, $s_{A'}$, turns out to be unfavorable for him.

The entrepreneur, if necessary, can take an action to mitigate adverse effects resulting from adoption of a new technology. More specifically, he can adjust his skill–mix h to

$$h' = h + \Delta \tag{6}$$

by bearing a cost of

$$C\left(\widetilde{y}, \Delta\right) = \left\{1 - \exp\left[-\frac{\gamma\left(\theta\right)}{2}\Delta^2\right]\right\}\widetilde{y} \tag{7}$$

where $\gamma\left(\theta\right) > 0$ and $\gamma'\left(\theta\right) < 0$ for any θ.

We can now express his net output or his entrepreneurial earnings, y^e, as

$$y^e = \max_{x,\Delta}\left\{\left[1 - \lambda\left(\theta, \Delta\right)\right]\widetilde{y}\left(x, \Delta\right)\right\} \tag{8}$$

where

$$\lambda\left(\theta, \Delta\right) = 1 - \exp\left[-\frac{\gamma\left(\theta\right)}{2}\Delta^2\right]$$

The cost of implementation of the advanced technology is captured by the term $\lambda\left(\theta, \Delta\right)$, and it decreases with θ. The term λ shows that, for given technical advancement x and shock ϵ, entrepreneurs with poor expertise in a nature of a production technology (i.e. high value of γ or low value of θ) must direct more scarce resources away from the productive use and towards narrowing a certain amount of a technical gap.

2.2 Optimal Decisions on Adoption and Implementation

This section describes entrepreneur's optimal decisions on adoption and implementation of an advanced technical knowledge. As described in the previous section, an entrepreneur makes a series of decisions so as to maximize his expected utility or equivalently his expected net (log) output. First, he sets a level of technology by choosing x. After x was chosen, a technical shock ϵ is realized and the skill–mix ideal is determined. Then, he observes a realized technical gap and decides how much he will close the technical gap by choosing Δ. Under the optimal choice of x and Δ, production of the good is carried out.

To ease our exposition, we assume that the initial level of technology A is the same for all entrepreneurs, and that the initial level of skill–mix h equals s_A, i.e. $h = s_A$, for all entrepreneurs. An optimal choice of x and Δ will be obtained by solving an entrepreneur's optimization problem backward. Given x and ϵ, an entrepreneur with θ solves

$$\max_{\Delta} A + x - \frac{1}{2}(x\epsilon - \Delta)^2 - \frac{\gamma(\theta)}{2}\Delta^2$$

The first order necessary condition for the optimality of Δ implies

$$\Delta = \left[\frac{1}{1+\gamma(\theta)}\right] x\epsilon \tag{9}$$

To derive an optimal amount of x, substitute equation (9) into the objective function of the entrepreneur with θ and calculate his expected utility. His optimization problem is then written as

$$\max_{x\in[0,\infty)} A + x - \frac{x^2}{2}\left[\frac{\gamma(\theta)}{1+\gamma(\theta)}\right]\sigma^2$$

The first order necessary condition for the optimality of x implies

$$x = \left[\frac{1+\gamma(\theta)}{\gamma(\theta)}\right]\frac{1}{\sigma^2} \tag{10}$$

Immediate implications for the optimal choice of Δ and x are as follows:

Proposition 1

(i) Entrepreneurs fill a larger fraction of their technical gap as a level of human capital is higher.

(ii) Entrepreneurs with higher human capital choose a more advanced technology.

Proof: (i) Since $x\epsilon$ is a technical gap and $\gamma(\theta) > 0$ for any θ, the term $\frac{1}{1+\gamma(\theta)}$ indicates a fraction of the technical gap an entrepreneur with θ tries to fill. The derivative of $\frac{1}{1+\gamma(\theta)}$ with respect to θ is given by $-\frac{\gamma'(\theta)}{[1+\gamma(\theta)]^2}$, which has a positive sign because of $\gamma'(\theta) < 0$ for any θ. (ii) Since $\frac{1}{1+\gamma(\theta)}$ increases with θ, $\frac{\gamma(\theta)}{1+\gamma(\theta)}$ decreases with θ, which implies its inverse, $\frac{1+\gamma(\theta)}{\gamma(\theta)}$, increases with θ. Therefore, x increases with θ. ■

Superior ability to analyze information about a nature of a production technology serves as to lower the marginal cost of filling a technical gap arising from adoption of a new technology, whereas the marginal benefit of filling a certain technical gap is independent of this ability. As a result, entrepreneurs with low γ can close the technical gap more without sacrificing scarce resources. Proposition 1.i thus suggests that $\gamma(\theta)$ measures entrepreneurial ability to hit or come closer to the ideal skill–mix. Since entrepreneur's inability to fill a technical gap causes a partial loss of benefits from adoption of an advanced technical knowledge, $\gamma(\theta)$ can be also interpreted as entrepreneurial ability to implement the advanced technical knowledge.

This ability in turn allows entrepreneurs to choose a more advanced technology. As shown in (10), an optimal choice of technical advancement, x, is inversely related to a fraction of the technical gap the entrepreneur intends to leave open, $\frac{\gamma(\theta)}{1+\gamma(\theta)}$. Superior ability to implement the advanced technology enables entrepreneurs to effectively mitigate potential adverse effects associated with adoption of an advanced technology, and it consequently encourages them to adopt a more advanced technology.

It is worthwhile to mention that entrepreneurial ability to adopt and implement an advanced technology described above, in its essence, corresponds to the concept of "allocative ability" introduced by Welch (1970). In his seminal work, allocative ability is referred to as worker's ability to acquire and decode information about costs and productive characteristics of other inputs, and to redirect scarce resources within the organization in response to changes in economic conditions.

We now turn our attention to implications of entrepreneurial capacity for their earnings. Substituting optimal solutions of Δ and x into the objective function, we obtain the expected value of maximized entrepreneurial log earnings as

$$E(\ln y^e) = A + \frac{1}{2\sigma^2}\left[\frac{1+\gamma(\theta)}{\gamma(\theta)}\right] \tag{11}$$

Differentiating equation (11) with respect to θ yield

$$\frac{\partial E(\ln y^e)}{\partial \theta} = -\frac{1}{2\sigma^2}\left[\frac{\gamma'(\theta)}{\gamma(\theta)^2}\right] > 0 \tag{12}$$

Entrepreneurial earnings thus increase on average with human capital. Since a determination of a technical gap is stochastic in this model, luck indeed affects entrepreneurial earnings but it plays only a secondary role in determination of entrepreneurial incomes. As we can see from equations (11) and (12), entrepreneur's capability to deal with uncertainty surrounding adoption of a new technology is a main source of the variation in entrepreneurial earnings. To see this point more clearly, consider an extreme case where the initial technology level A is the best technology available so that there is no room for technical advancement. In this case, entrepreneurial (log) earnings equal A regardless of a level of human capital they posses, so there is no variation in entrepreneurial earnings.

We can summarize the discussion above as follows. Technical progress is an important channel for the creation of profitable opportunities and entrepreneurs earn rewards for their performance to adopt and implement an advanced technology. These entrepreneurial rewards increase with their capacity of dealing with uncertainty surrounding adoption and implementation of the advanced technology.

2.3 Individual's Choice of Employment Status

Both paid and entrepreneurial earnings are related to a level of human capital (see equations (2) and (11)). We now examine implications of a difference in level of human capital for an individual's choice about employment status as well as properties of the resulting earnings distribution. Since our data do not allow us to examine testable implications in a general equilibrium framework, we do not exploit such implications here and therefore we do not attempt to close the model in order to avoid unnecessary complications.

In this model, an individual chooses to be an entrepreneur if his entrepreneurial income exceeds his alternative paid wage. Therefore, an individual with human capital θ becomes an entrepreneur if the following condition is met:

$$A + \frac{1}{2\sigma^2}\left[\frac{1+\gamma(\theta)}{\gamma(\theta)}\right] \geq w\theta$$

Otherwise, he selects to be a paid employee. As we can see from the inequality just above, properties of function γ affect individual's choice about employment status. That is, an emerging sorting pattern crucially depends on how one's underlying human capital is transformed into entrepreneurial capacity for adoption and implementation of an advanced technology.

Proposition 2
(i) (pooling sorting pattern) If $\frac{\gamma''}{\gamma'} \leq 2\frac{\gamma'}{\gamma}$*, then individuals with lower level of human capital becomes an entrepreneur, whereas those who possess a higher level of human capital becomes a paid employee.*

(ii) (separating sorting pattern) If $\frac{\gamma''}{\gamma'} > 2\frac{\gamma'}{\gamma}$ *and if* $w > -\frac{1}{2\sigma^2}\frac{\gamma'}{\gamma^2}$ *for some* θ*, then individuals become paid employees when their human capital is moderate, whereas there are two types of entrepreneurs: entrepreneurs with high human capital and entrepreneurs with low human capital.*

Proof: See Appendix.

To see proposition 2 more clearly, consider a special case where $\gamma(\theta) = \theta^{-\eta}$ with $\eta \geq 0$. Then, the expected value of entrepreneurial earnings is simply given by

$$E(\ln y^e) = A + \frac{1}{2\sigma^2}\left[1 + \theta^{\eta}\right]$$

Thus, expected entrepreneurial earnings are a convex function of θ if $\eta \geq 1$ and are a concave function of θ if $\eta \leq 1$. Two different sorting patterns are depicted in figure?, depending on a value of parameter η. When its relevance of human capital to entrepreneurial capability of adopting and implementing an advanced technology is weak, individuals with low human capital select to be entrepreneurs and individuals with high human capital becomes paid workers. What we call "pooling sorting pattern" is illustrated in Figure 1.a. On the other hand, the sorting pattern depicted in Figure 1.b is labeled as "separating sorting pattern" and it emerges when human capital is relatively more valued in entrepreneurship, in the sense that a percentage difference in level of human capital is translated into more than one percentage difference in entrepreneurial capacity. As we can see from the figure, there are two types of entrepreneurs in this case. One type of entrepreneurs possesses exceptionally a high capacity and produces the good by using advanced technologies. On the other hand, the other type of entrepreneurs does not have capability to deal with advanced technologies and ends up with employing out–of–date technologies.

Figure 1 (a)

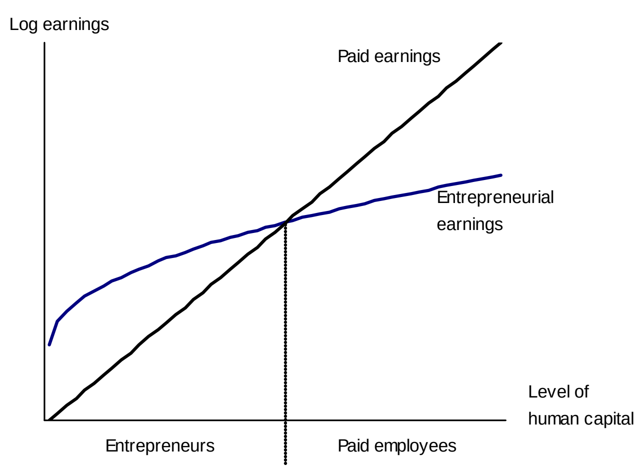
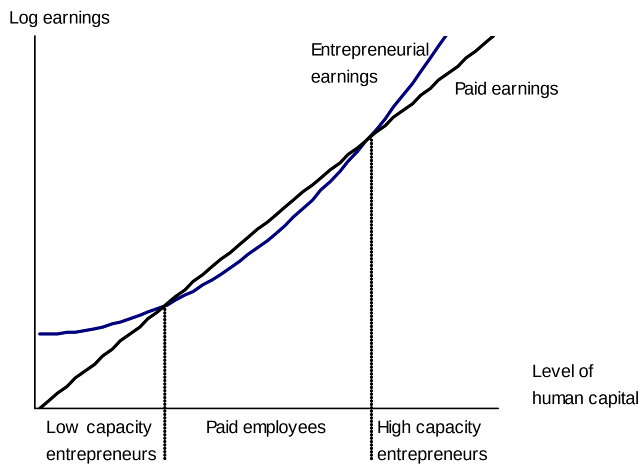


Figure 1 (b)



The discussion above is also led us to infer that the overall earnings distribution is influenced by each individual's rational choice about employment status. It is straightforward to see that we have the following testable implications:

Proposition 3

(i) Suppose that a pooling sorting pattern prevails. The entrepreneurship premium –the earnings of entrepreneurs relative to the earnings of paid employees– is negative.

(ii) Suppose that a separating sorting pattern prevails. The entrepreneurship premium for high–capacity entrepreneurs is positive, whereas the entrepreneurship premium for low–capacity entrepreneurs is negative. A sign of the overall entrepreneurship premium depends on a distribution of human capital.

Proof: See Appendix.

This proposition offers important insights pertaining to empirical findings in recent entrepreneurship studies that identify entrepreneurs with independent business owners (i.e. self–employed). These studies tend to find a negative entrepreneurship premium and then propose several hypotheses to rationalize this finding (e.g. Hamilton, 2000, Astebro and Thompson, 2007). To a greater or lesser degree, the hypotheses in these studies presume that entrepreneurs (self–employed) do not significantly contribute to economic change and entrepreneurial activities (self–employment activities) do not have much economic value.

As shown in proposition 3, the model presented here also predicts that the overall entrepreneurship premium is negative when human capital does not play a vital role in entrepreneurial activities or when a positive entrepreneurship premium of high–capacity entrepreneurs is outweighed by a negative entrepreneurship premium of low–capacity entrepreneurs. In either case, this prediction will result in highlighting low–capacity entrepreneurs whose entrepreneurial activities do not require the regular utilization of advanced technical knowledge and whose average income is lower than the average income of paid employees. Indeed, this image of entrepreneurs is in accord with owners of corner store type businesses, for advanced technical knowledge is not necessarily required to perform their jobs and these businesses are likely to be operated by educationally disadvantaged individuals.

It deserves to receive attention that proposition 3 also points out a potential pitfall of characterizing entrepreneurs based on the evidence of a negative total entrepreneurship premium alone. That is, when a separating sorting pattern actually emerges, aggregating over two groups of entrepreneurs may lead to masking a nature of entrepreneurial activities performed by high–capacity entrepreneurs. By the same token, looking at only successful entrepreneurs without any micro–foundation tends to blur a source of entrepreneurial functions. Thus, this model provides a unified treatment of these two different kinds of entrepreneurs in a simple manner and it bridges a gap between "heroic" entrepreneurs, envisioned mostly by theoretical studies of entrepreneurship, and "desperate" entrepreneurs, documented frequently in empirical studies.

Which sorting pattern emerges in reality is purely an empirical question. When a pooling sorting is a dominant form, the entrepreneurship premium should be negative regardless of whether we distinguish high–capacity and low–capacity entrepreneurs. On the other hand, the entrepreneurship premium should be positive for high–capacity entrepreneurs and be negative for low–capacity entrepreneurs when a separating sorting pattern takes place. Thus, we can empirically distinguish two sorting patterns by dividing individuals into two groups depending on a level of human capital and then looking at the entrepreneurship premium separately. In addition, if a separating sorting pattern actually emerges, we must have the following implication for earnings differentials within each employment status group:

Corollary 4
Suppose that a separating sorting pattern emerges. The earnings differential between high–capacity and low–capacity entrepreneurs is larger than the expected earnings differential between high–capacity and low–capacity paid employees.

3 Empirical Analysis

3.1 The Data

We use the data from the Scientists and Engineers Statistical Data System (SESTAT) for the years 1995, 1997 and 1999. SESTAT is an integrated data system of information about a representative sample of individuals living in the United States who obtained at least a bachelor's degree and are trained as or working as scientists or engineers. The National Science Foundation (NSF) collected a broad range of information about the demographic, educational, and employment characteristics of these scientists and engineers mainly from three national surveys: The National Survey of College Graduates (NSCG), The National Survey of Recent College Graduates (NSRCG) and The Survey of Doctor Recipients (SDR).

The empirical examination of the highly–educated workforce in the science and engineering fields is indispensable for the main purpose of this study, not only because such a highly–educated workforce has not been comprehensively examined in past studies of entrepreneurship, but also because we believe that highly–educated entrepreneurs are more likely to engage in job activities closely relating to adoption and implementation of advanced technologies than educationally disadvantaged entrepreneurs. Thus, the empirical investigation of entrepreneurs in SESTAT is more appropriate from our viewpoint than analyzing entrepreneurship by use of general population surveys. Notice that, as our theoretical argument demonstrates, higher education itself does not necessarily favor self–employed in one way or another. It is also noteworthy that SESTAT contains such a large number and a broad scope of observations that the data enable us to investigate general characteristics of highly–educated entrepreneurs systematically rather than presenting some anecdotal evidence.

One of the difficulties in studying entrepreneurship is rooted in the problem of how to identify entrepreneurs. It has been common in applied empirical work to identify entrepreneurs with independent business owners (self-employed), based on the idea that they derive earnings by performing economic activities at their own will and at their own risk (see Parker, 2004). To avoid potential controversy arising from ad hoc identification of entrepreneurs as well as make our results comparable with those of past studies, this study follows the common practice by identifying entrepreneurs with self–employed.

In our theoretical study entrepreneurs are characterized as economic agents who make decisions on adoption and implementation of advanced technical knowledge. Of course, using self–employment status as an approximation to the entrepreneurs described in the model part is not perfect. Nonetheless, it still sounds reasonable because self–employed are more likely to take full responsibility for decisions on adoption and implementation of advanced technologies than paid employees working for someone else. In NSF surveys that form the basis of SESTAT data sets, respondents were asked to report a type of their principal employer. Those who reported either "self–employed in own incorporated business, professional practice or farm" or "self–employed in own not incorporated business, professional practice or farm" are categorized as self–employed in this study, and the rest of the workforce in our sample is categorized as paid employees.

We focus our empirical analysis on scientists and engineers aged 65 or less, reporting non-zero annualized basic salary and working full time, where "full time" is defined as working weekly for at least 30 hours and annually for at least 48 weeks. We thus exclude retired, unemployed, part-time workers and also those who report zero basic salaries. This is dictated by our desire to estimate returns to self-employment (entrepreneurship) as full-time, rather than part-time or after-retirement activity. Also, since one of our main purposes is to examine returns to entrepreneurship relative to corresponding paid work, we exclude from our sample individuals in occupations where self-employment is a rare case. For example, there are almost no self-employed among teachers, so we exclude teaching occupations from our sample. As suggested in the previous literature, we also exclude health-related occupations, lawyers and judges, as well as agricultural occupations because earnings in those are hard to compare with other occupations. While excluding these occupations is in line with common practice, we did check the robustness of our results reported below by including those occupations, and confirmed that our main conclusions do not qualitatively change regardless of whether these professionals are included or not. The full list of occupations in our sample is provided in Appendix.

For the cross–sectional analysis, we pool the data from 1995, 1997 and 1999 SESTATs to carry out in-depth empirical analysis within as well as across occupational groups. The total number of observations used in this study is 140,946. Of the total number of observations, 8,662 pertain to self-employed individuals, while 132,284 observations are on paid employees. When adjusted using population weights provided by SESTAT, the share of self-employed observations in the total is 8.82 percent, which is a little bit less than the share of business owners in the total number of non–agricultural employees in the United States.

Table 1 presents the basic summary statistics on self-employed and paid workers in our sample. In line with findings in previous studies, self-employed in our sample are more likely to be male and white than paid workers, and they have a slightly higher educational attainment, as measured by the share of individuals with doctoral degrees. An average self-employed is also more than 6 years older than an average paid worker (46.4 versus 40.3 years).

Respondents to NSF surveys were asked about the relationship between the current job and the highest educational degree they have earned (with three choices, closely related, somewhat related, and not related at all). As Table 1 shows, 46.5 percent of self-employed hold jobs closely related to their highest educational degree earned, whereas the corresponding number for paid employees is 53.6 percent. In the following empirical analysis we will exploit this self-reported measure of the importance of specialized knowledge in the current job.

[Table 1 here]

In this study we measure paid and self–employment returns by a basic earned income, on the grounds that it is the price paid for one's human capital (Juhn, Murphy, and Pierce (1993)). The NSF survey respondents were asked to report their basic annualized salary for the survey year, excluding bonuses, overtime or additional other compensations. If not salaried, they were asked to estimate their earned incomes, excluding business expenses.[1] Summary statistics on annualized earned income are reported in Table 2, where 1997 and 1999 earnings have been deflated by the consumer price index, with 1995 as the base year. The problems inherent in measuring self-employed earnings are well-known and have been discussed in the literature (e.g. Hamilton, 2000, Parker, 2004), so we do not dwell upon those here.[2] Panel A of Table 2 shows that the mean annualized income of self-employed in our sample is $63,945 and that of paid workers is $57,057. In comparison, the reported average income of self-employed in the sample of Evans and Leighton (1989) study is about $16,687 and that of paid workers is $19,695, which is much lower even after taking account of inflation. Such a huge gap in unconditional mean of annualized income between their and our samples simply reflects the fact that our sample contains a highly-educated workforce only.

[Table 2 here]

Panel B of Table 2 presents summary statistics of annualized income by job relation to education, separately for self-employed and paid employees. In all three categories, the unconditional mean of self-employed salary is higher than that of paid workers. More importantly, an interesting fact can be found when we look at unconditional means of self-employed

[1] The survey question regarding earnings intends respondents to report a net profit when they are not salaried workers. There is however a possibility that some self–employed reported just retained earnings. In this respect, total self–employment earned incomes are in general under–reported.

[2] It appears that the measure of self-employed income in SESTAT comes closest to the "draw" measure in Hamilton (2000).

salary and paid workers separately. According to Panel B of Table 2, self-employed whose job is closely related to their education earn the most among the three categories, and these self-employed earn approximately 40 percent more than self-employed whose job is not related to their education at all. On the other hand, the unconditional mean salary of paid employees with job closely related to their education is about the same as that of paid employees with job somewhat related to their education. These paid workers earn about 25 percent more than paid employees whose job is not related to their education at all. Thus, our summary statistics appear to show that knowledge or skills acquired through formal education have a larger impact on productivity of self-employed than that of paid employees. This observation is to be examined formally in regression analysis below.

3.2 The Examination of Model's Implications

3.2.1 Impacts of Expertise on Earnings of Self–Employed and Paid Employees

We first estimate earnings equations of self-employed and paid workers separately to see how observable characteristics affect the level of (log) earnings of each category. In particular, we are interested in investigating whether a proxy variable for human capital has large impacts on self–employed earnings or on paid wages. For these estimations, we employ an earnings function similar to the one developed by Mincer (1974) and widely used in the subsequent literature:

$$\ln y = x\beta + e \tag{13}$$

where y is an annualized income, x is a row vector of explanatory variables, β is a column vector of parameters and e is a disturbance term.

Our basic earnings equation includes potential labor market experience (age – years of education – 6), tenure (the number of years in a current job), education levels, gender, white–race, marriage status and occupational dummies. In addition to these variables, a dummy variable indicating one's job relation to a field of his/her highest educational degree is included in the earnings equation. For convenience, this variable is labeled as "education-job-relation" (EJR) in the subsequent analysis. EJR variable takes on 1 if one's job is closely related to his/her highest educational degree and 0 if one's job is somewhat related or not related to his/her highest educational degree at all. See Appendix for the description of explanatory variables.

Table 3 presents estimation results from censored regressions under two different specifications.[3] As we can see, almost all the estimated coefficients in these regressions have the expected signs and are statistically significant. A higher educational level increases earnings of both self-employed and paid workers, and male workers in both categories earn more than their counterpart of female workers. Table 3 also shows that, holding other things fixed, the earnings functions in both categories are increasing and concave with respect to labor experience and tenure. In self-employment jobs, tenure effects are larger than labor experience effects and the converse statement holds for paid jobs. These are the standard results in the literature.

[Table 3 here]

We obtain interesting insights when looking at effects of education-job-relation on the level of (log) earnings. Because of mainly data limitations, past studies have not been unable to systematically examine how earnings of self-employed or those of paid workers are affected by the fact that their formal education is closely related to their jobs. This is therefore considered to be a new element of this study.

According to our estimation results in column (I) of Table 3, the conditional expected earnings of both self-employed and paid workers increase when one's job is closely related to his/her highest educational degree. This result would not come as surprise because we expect one's productivity to rise when he/she has considerable expertise in his/her job. There is however a substantial difference in magnitude of this effect between self-employed and paid employees. For self-employed, our estimated coefficient of EJR variable under specification (I) is 0.201. Self-employed earnings thus increase on average by 22.3 percent when they hold self-employment jobs closely related to their formal education. This EJR effect on self–employment earnings cannot be overlooked because its estimated effect is similar in magnitude to 10 years of tenure in self–employment jobs. On the other hand, the corresponding number for paid workers is only 3.8 percent. This appears to suggest that returns to one's specialized knowledge are compressed in paid wages. We also found that these results were robust to several specifications of (13), including one that attempts to account for potential selectivity biases (See Appendix).

To examine effects of job–education–relation on earnings more closely, take a look at column (II) of Table 3 where interaction terms of education–job–relation with educational

[3] We implemented censored regressions since earnings recorded from the NSCG are top-coded at $150,000. Earnings recorded from other two surveys do not have this problem, and the OLS and censored regressions produce very similar results in any case

level are added to the basic earnings equation. For self–employed with a doctorate degree, the estimated coefficient of EJR variable interacted with doctorate education dummy is 0.103 and statistically significant, while the corresponding estimate for paid employees is 0.007 and insignificant. In other words, the value of doctorate education in self–employment jobs depends on whether their job is closely related to his/her doctorate education, whereas this effect is totally absent in paid employment jobs. According to our estimates, self–employed whose job is closely related to their doctorate education earn approximately 31 percent more than self–employed whose job is not related to their doctorate education. A similar calculation shows that this earnings differential for paid employees with a doctorate degree is 4.1 percent. Furthermore, when we compare doctorate degree recipients who hold jobs closely related to their education and bachelor's degree holders with jobs not related to their education, the estimated earnings differentials between them are about 61 percent for self–employed and 48 percent for paid employees.

It is often argued that entrepreneurial skills are non–academic in nature, based on the evidence that the rate of return to education for self–employed is lower than the one for paid employees (e.g. Van der Sluis, Van Praag and Vijverberg, 2003). Our analysis however points out that this conclusion may be premature. We could conclude, based on estimation results in column (I) of Table 3, that human capital plays less significant roles in the determination of self–employment earnings than in that of paid wages if we completely ignored effects of EJR and looked at only effects of education. But, as demonstrated above, this conclusion becomes questionable when effects of education–job–relation are taken into consideration. This discussion leads us to consider a question of what roles higher education plays in production activities. Welch (1970) emphasizes that education plays a role in enhancing a worker's ability to learn and process information about characteristics of productive means rather than increasing capability of doing physical work per a given time. It is plausible that allocative ability acquired through formal education is valued more in self-employment activities than in paid-employment jobs since self–employed are more likely to be involved in a decision process of an input-output choice, technical adoption, and so forth.

All individuals in our sample have completed post secondary education. Some of them are holding a job closely related to their education and others are working outside of their education field. It probably would be safe to argue that, for a given education level, the former type of workers has greater knowledge or skills regarding their job than the latter type of workers, and that doctorate degree recipients of the former type have the greatest expertise in their job among all categories of workers. Our estimation results therefore can be interpreted as follows.

Evidence 1

For a highly–educated workforce in science and engineering fields, one's expertise or human capital has larger impacts on self–employment earnings than on paid wages.

This finding is in line with a prediction offered by our theory. While this finding can be observed under a pooling sorting pattern, we must observe it under a separating sorting pattern because the prediction under the separating sorting pattern survives no matter how human capital is distributed. Since the finding is not inconsistent with our theory, we proceed our analysis to examine validity of our theory and to determine an actual sorting pattern in our sample.

3.2.2 Impacts of Expertise on Earnings Differentials between Self–Employed and Paid Employees

We now examine earnings differentials between self-employed and paid employees in order to infer an actual sorting pattern in our sample. This section employs Hamilton's methodology (2000) to calculate entrepreneurship premia based on the discounted present value of estimated lifetime earnings. In doing so, we first estimate an earnings equation at several locations of the earnings distribution separately for paid employees and two different categories of self–employed, and then project earnings profiles by changing years of labor experience and tenure simultaneously. These profiles illustrate the joint impact of labor market experience and tenure on earnings of individuals who have spent a given number of years in the labor market and start a new business as self–employed or a new job as a paid employee. An individual's working lifetime is assumed to be 35 years, and the discount rate is set equal to 3 percent per year to calculate these earnings differentials. For example, if we consider workers with 10 years of labor market experience who start a new business or job, we try to estimate the discounted present value of their cumulative earnings in the remaining 25 years of their lifecycle by assuming that they do not change their business or job again, and then these estimations are used to calculate earnings differentials between self–employed and paid employees.

Figure2

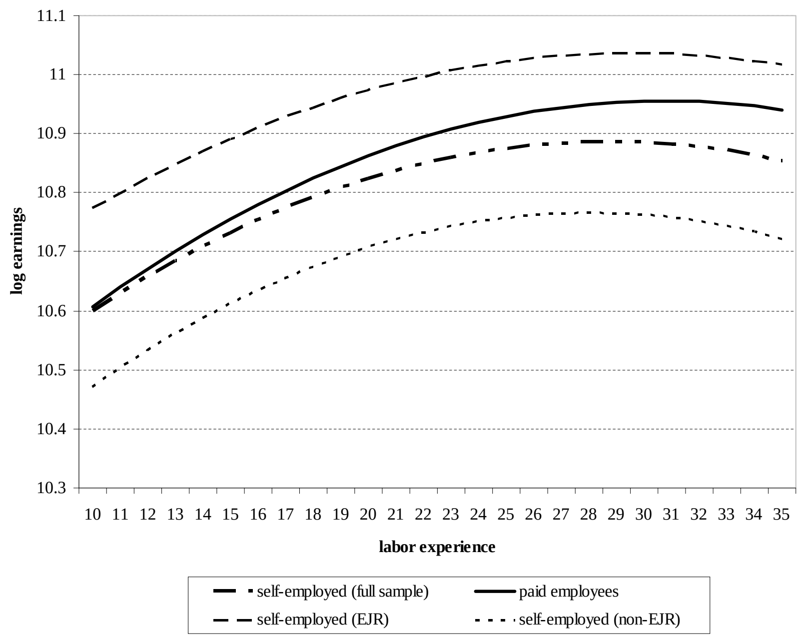


Figure 2 plots earnings profiles of the expected self-employment incomes as well as the expected paid wages for workers entering a new business or job after 10 years of labor market experience. In Figure 2, three different earnings profiles are projected for self–employed: self–employed (full sample) indicates that all self–employed in the sample are used to estimate the earnings equation. Similarly, the earnings profile of self–employed (EJR) utilizes self–employed whose jobs are closely related to their education while the earnings profile of self–employed (non–EJR) makes use of self–employed with jobs not related to their education.

The importance of disaggregating self–employed according to a degree of one's expertise in job, approximated by EJR variable here, is illustrated in Figure 2. As we can see from the figure, the predicted earnings profile of self–employed in EJR category is above that of paid employees, but the relation is reversed for self–employed in non–EJR category. When we aggregate over these two types of self–employed, the self–employed earnings profile for the full sample is located below that of paid employees. Hence, it would be reasonable to start searching for reasons of a "negative" entrepreneurship premium around non–monetary motives if we merely conducted the aggregate analysis. Such an aggregate analysis however may result in masking true characteristics of high–capacity self–employed, mainly motivated by pecuniary returns to their economic activities, even if these self–employed are present in a sample at hand. Note also that, as our model demonstrated, the disaggregate analysis will not necessarily produce additional insights, especially, if human capital is relatively unimportant in self–employment jobs or if high–capacity self–employed are nonexistent in a sample or a target population of our interest.

Table 4 presents estimates of the entrepreneurship premium for four different years of prior labor market experience at which a new business or job is to be started. The censored regression is carried out to estimate the expected value of entrepreneurship premium while quantile regression models are employed to measure the entrepreneurship premium at median as well as upper and lower quartiles.[4]

[Table 4 here]

We begin by taking a look at estimates for the expected value of entrepreneurship premium. It is noticeable that the mean entrepreneurship premium exhibits a systematic difference between self–employed in EJR category and those in non–EJR category. Regardless of prior labor experience, the expected value of entrepreneurship premium is positive for a group of EJR self–employed, whereas it is negative for self–employed in non–EJR group. For example, during their subsequent lifetime after starting a new business or job, the average self–employed in EJR category with 10 years of prior labor experience are estimated to earn 11.8 percent more than the average paid employees with the same prior labor experience. On the other hand, the corresponding earnings differential between the average self–employed in non–EJR category and the average paid employees is negative 13 percent. Except for 0 year of prior labor experience category, the expected values of the entrepreneurship premium for the full sample are negative ranging from negative 0.6 percent to negative 7.7 percent, though the magnitude of these negative premia is much smaller than Hamilton's estimation. We can also observe that the expected values of entrepreneurship premium in all categories are monotonically decreasing with years of prior labor experience.

Consider next the entrepreneurship premium measured at different locations of the earnings distribution. Qualitative features of the entrepreneurship premium estimated at the 25th percentile and median are the same as those of the mean entrepreneurship premium. That is, the estimated entrepreneurship premium is positive for self–employed in EJR category and negative for self–employed in non–EJR. On the other hand, the entrepreneurship premium measured at the 75th percentile is all positive regardless of self–employed categories as well as prior labor experience. This suggests that successful self–employed earn more than its counterpart of paid employees.

We can summarize our findings as follows.

[4] It is well known that quantile regression models are less prone to top–coded problems than the ordinary least squares regression. See Buchinsky (1998) for the detailed discussions.

Evidence 2

(i) For self–employed whose jobs are closely related to their education, the expected entrepreneurship premium is positive, ranging from 6.5 percent to 25.3 percent. In addition, the estimated entrepreneurship premium is also positive when measured at the 25th, median and 75th percentile.

(ii) For self–employed whose jobs are not related to their education, the expected entrepreneurship premium is negative, varying from negative 17.2 percent to negative 10.8 percent. The estimated entrepreneurship premium is negative when measured at the 25th percentile and median, but it is positive at the 75th percentile.

We now match Evidence 2 with predictions of our model in order to deduce an actual sorting pattern. As evident in Evidence 2, there seems two types of self–employed in our sample. When we compare earnings of paid employees with those of EJR self–employed (self–employed whose jobs are closely related to their education), our estimation of the entrepreneurship premium reveals that these self–employed outperform paid employees in terms of earning capacity not only when it is measured at the mean but also at several important percentiles, 25th, 50th and 75th, of the earnings distribution. This finding thus suggests that EJR self–employed corresponds to high–capacity entrepreneurs in the model part. On the other hand, the entrepreneurship premium is negative for non–EJR self–employed (self–employed whose jobs are not related to their education) when it is measured at the mean, 25th percentile and median. Non–EJR self–employed are by and large in line with low–capacity entrepreneurs in the model part. Our model tells us that we would not observe opposite signs of the entrepreneurship premium by disaggregating self–employed into EJR and non–EJR categories if a pooling sorting pattern actually took place in our sample, but we should if a separating sorting pattern actually emerges. Furthermore, under the separating sorting pattern, self–employed earnings vary with human capital to a larger extent than paid wages. This has been already confirmed by Evidence 1. Hence, we infer from Evidence 1 and 2 that a separating sorting pattern is likely to be an actual sorting pattern.

3.3 The Evaluation of the Model in Comparison with Non–Monetary Compensation Hypothesis

Our model under the separating sorting pattern is quite successful in explaining both Evidence 1 and 2. Of course, this alone does not allow us to rule out other hypotheses of entrepreneurship proposed in the literature. As mentioned in introduction, it is a widely accepted hypothesis that self–employed sacrifice monetary returns in exchange for non–monetary benefits. In this study, we focus on examining whether our model or non–monetary compensation hypothesis fares better with evidence from our data, since sharp implications regarding earnings differentials are available in both hypotheses and their discussions center around characteristics of entrepreneurs.[5]

3.3.1 An Evaluation Based on Estimated Entrepreneurship Premium

Several versions of non–monetary compensation hypothesis have been offered as a main explanation for a negative entrepreneurship premium found in a number of empirical studies (e.g. Hamilton, 2000, Moskowitz and Vissing-Jørgensen, 2002, and Åstebro and Thompson, 2007). As pointed out in the labor literature, especially by Rosen (1986), labor markets can be viewed as places in which not only labor services but also job attributes are exchanged. Applying this idea to our context, self-employment jobs can be viewed as a composite good which price consists of the reward to human capital and the cost incurred to obtain preferable job attributes such as being your own boss or performing a variety of tasks. Keeping this view in mind, this section examines estimation results presented in section 3.2.

Our estimation using the full sample showed a negative entrepreneurship premium, which is in line with findings of past studies. But the disaggregate analysis revealed a positive premium for self–employed who hold a job closely relate to their education on the one hand, and a negative premium for self–employed who is working outside their educational fields on the other hand. It is this disaggregate analysis of highly–educated self–employed that provides us with the most suggestive empirical results.[6] All self–employed may be enjoying

[5] Implications for earnings differentials are ambiguous for the hypothesis based on incentive–oriented paid contract such as in Lazear and Moore (1984) or the argument regarding cost and benefit sharing of human capital investments. These theories usually assume that lifetime earnings are equalized across different occupations in equilibrium. Needless to say, these theories are important to explain how earnings profiles evolve differently between self–employed and paid employees.

[6] The sample examined in Hamilton (2000) consists of less than 9,000 observations, fewer than 1,000 of them on self-employed individuals. Just 22% of paid workers and 27% of self-employed have 4 years of college or more under their belts, making disaggregated analysis of returns to entrepreneurship for highly educated

non–monetary benefits to some extent, but our analysis suggests that highly–capacity self–employed (EJR self–employed) in our sample would still choose to be self–employed even if non–monetary benefits were totally absent in self–employment jobs. That is, monetary returns to their productive activities guide these self–employed into the self–employment sector. For low–capacity self–employed (non–EJR self–employed), we are not able to deny a possibility that non–monetary motives play a significant role at this stage. These self–employed may be actually paying for purchasing preferable attributes associated with self–employment jobs, so that they would switch to paid jobs if its price is too high or if there does not exist relative non–monetary benefits in self–employment activities at all.

The non–monetary compensation hypothesis is also hard to reconcile with the fact that self–employed earnings are largely affected by EJR variable. One's satisfaction from self–employment jobs may be correlated to how closely his/her job is related to his/her formal education. For example, self–employment jobs may allow one to choose or devote much time to a work activity that satisfies his/her interests developed by higher education.[7] But, if this is the case, it would be natural to consider that EJR self–employed are enjoying this type of self–employment characteristics more than non–EJR self–employed, and the former type is willing to sacrifice more monetary returns than the latter. As in Åstebro and Thompson (2007), however, non–EJR self–employed may be gaining additional non–monetary benefits by carrying out various tasks, provided that EJR variable is a good proxy for taste of job variety.

Our discussion above leads us to cast a doubt on non–monetary compensation hypothesis as a main explanation for behaviors of highly–educated self–employed in our sample, at least, for self–employed who have considerable expertise in their job. Still, it is too early to reach a conclusion because our argument is acceptable only if there is no self–selection issue involved. The entrepreneurship premium just compares earnings of different groups of individuals: a group of "actual" self–employed and a group of "actual" paid employees. On the other hand, the non–monetary compensation hypothesis compares potential earnings of the "same" individual as self–employed and as a paid employee, and then argues that self–employment earnings of actual self–employed is lower than alternative or potential paid earnings of these actual self–employed. That is, actual self–employed would be able to earn more if they were

part of the sample all but impossible. Similarly, Mosckowitz and Vissing-Jorgensen (2002) note that while they would like to estimate returns to entrepreneurial private equity across industries, the small number of observations makes it impossible (p. 761).

[7] This argument is based on the following idea. A job consists of several activities. These work activites are more difficult to be unbundled under paid employment jobs, perhaps because of a paid wage contract, than self–employment jobs.

forced to switch to paid employees. Most empirical studies of entrepreneurship, including Hamilton (2000), report that there is no conclusive evidence of self–selection, although this does not necessarily mean that we do not find effects of self–selection in our sample. We are thus led to set up a counterfactual setting and examine ability of our model and non–monetary compensation hypothesis to explain behaviors of highly–educated self–employed.

3.3.2 An Evaluation Based on Structural Probit Model

The non–monetary compensation hypothesis argues that a person becomes self–employed in spite of the fact that the same person can earn more as a paid employee than as self–employed. On the other hand, our model presumes that a person becomes self–employed because the same person can earn more as self–employed than as a paid employee. This section utilizes a counterfactual setting and tries to directly answer whether an individual's decision on self–employment status is primarily made based on pecuniary returns or on non–pecuniary benefits. A structural probit model is our analytical tool in this section.[8]

To build up a counterfactual setting, let y^S denote potential earnings of a person when he is self-employed and y^P denote potential earnings of the same person when he is a paid employee. Assume that potential log earnings are linearly related to a vector of observable variables x and unobservable v as

$$\ln y^j = \mu^j + x\beta^j + v^j \text{ for } j = S \text{ or } P \tag{14}$$

where μ and β are parameters and we assume that $E\left(v^j \mid 1, x\right) = 0$ for $j = S$ or P.

The total net benefit of being self-employed is given by

$$D^* = z\pi + u \tag{15}$$

where a vector variable of z includes x and other observable variables that contribute to self-employment benefits, and u indicates unobservable self-employment benefits. Individuals rationally select to be self-employed if the total net benefit from self-employment jobs exceeds zero. By letting dummy variable D take on 1 if a person is actually self-employed and 0 if he is a paid worker, we can compactly express the relation of the total net benefit to self-employment status as

$$D = 1\left\{D^* \geq 0\right\} \tag{16}$$

[8] Refer to Borajas and Bronars (1989) and Bernhardt (1994) for the detailed discussions on applications of this methodology to self–employment studies.

where $1\{\cdot\}$ is an indicator function.

To deal with the potential endogenous problem in a simple way, we assume that $\left(v^P, v^S, u\right)$ is mean-independent of and follows a trivariate normal distribution:

$$\begin{pmatrix} v^P \\ v^P \\ u \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_P^2 & \sigma_{PS} & \sigma_{Pu} \\ \sigma_{PS} & \sigma_S^2 & \sigma_{Su} \\ \sigma_{Pu} & \sigma_{Su} & \sigma_u^2 \end{pmatrix}\right] \tag{17}$$

Equations (14), (15), (16), and (17) represent our econometric model. Earnings equations of self–employed and paid employees are estimated separately by accounting for potential self–selection biases. We then use these estimates to predict potential earnings of each person as self–employed and as a paid employee. That is, we obtain, for individual i who actually becomes self–employed,

$$\begin{aligned} \ln \widehat{y}_i^S &\equiv E\left(\ln y^S \mid x_i, z_i, D_i = 1\right) = \mu^S + x_i\beta^S - \frac{\sigma_{Su}}{\sigma_u}\left[\frac{\phi\left(z_i\pi\right)}{\Phi\left(z_i\pi\right)}\right] \\ \ln \widehat{y}_i^P &\equiv E\left(\ln y^P \mid x_i, z_i, D_i = 1\right) = \mu^P + x_i\beta^P - \frac{\sigma_{Pu}}{\sigma_u}\left[\frac{\phi\left(z_i\pi\right)}{\Phi\left(z_i\pi\right)}\right] \end{aligned} \tag{18}$$

where $\phi(\cdot)$and $\Phi(\cdot)$ indicates standard nomal density and cummulative distribution functions, repsectively. For individual k who actually becomes a paid employee, predicted earnings eqations are

$$\begin{aligned} \ln \widehat{y}_k^S &\equiv E\left(\ln y^S \mid x_k, z_k, D_k = 0\right) = \mu^S + x_k\beta^S + \frac{\sigma_{Su}}{\sigma_u}\left[\frac{\phi\left(z_k\pi\right)}{1-\Phi\left(z_k\pi\right)}\right] \\ \ln \widehat{y}_k^P &\equiv E\left(\ln y^P \mid x_k, z_k, D_k = 0\right) = \mu^P + x_k\beta^P + \frac{\sigma_{Pu}}{\sigma_u}\left[\frac{\phi\left(z_k\pi\right)}{1-\Phi\left(z_k\pi\right)}\right] \end{aligned} \tag{19}$$

The structural probit model now can be expressed as

$$D^{**} = \eta\left(\ln \widehat{y}^S - \ln \widehat{y}^P\right) + w\gamma + \epsilon \tag{20}$$

$$D = 1\{D^{**} \geq 0\}$$

The predicted earning difference, $\ln \widehat{y}^S - \ln \widehat{y}^P$, captures monetary returns from self–employment jobs relative to monetary returns from paid jobs if a person performed both self–employment and paid jobs in a hypothetical world. This term will positively affect an individual's decision on being self–employed if individual's decision on self–employment status is primarily made based on pecuniary returns. Thus, if the coefficient of the earnings difference in the structural probit model, η, is estimated to be positive, it is an indication that pecuniary returns are a primary motive for being self–employed and we are led to cast a doubt on non–pecuniary motives.

Table 5 reports marginal effects on being self–employed, which are estimated from our structural probit model (See Appendix for estimated earnings equations with self–selection corrected terms). Since this estimation uses cross–sectional data, it is appropriate to interpret each variable in the probit model as a factor affecting the probability that individuals are self–employed rather than paid employees. Specification (II) uses the earnings equation specified in column (II) of Table 3, whereas EJR variable is dropped under specification (I). Variables of certification and U.S. citizenship are included in the decision equation (15) or (20) along with variables appearing in the earnings equation.[9] These two variables affect a person's decision on self–employment status but they do not seem to affect the earnings equations directly (See Appendix for the more detailed discussion). We also tried several specifications by including other variables such as parent's education or employer's locations in the equations (14) and (15). Such variables appeared not to affect the earnings equations nor the decision equation.

[Table 5 here]

As we can see from Table 5, the estimated coefficient of the earnings difference is positive under both specifications and statistically significant at the conventional significance level. Table 5 also shows that the marginal effect of the potential earnings differential on self–employment status is larger than effects of certification and U.S. citizenship. More importantly, the impact of potential earnings differentials on self–employment status become larger when education–job–relation is included in the earnings equation. This point is further checked by examining specification (III) where individuals are more finely classified in terms of education–job–relation.[10] When controlling for effects of education–job relation, monetary motives seem pronounced more strongly. We also conduct a similar analysis by dividing our sample into EJR and non–EJR groups because the negative entrepreneurship premium

[9] Certification variable is a dummy variable that takes on 1 if licensing or certification is recommended or required in one's occupation and takes on 0 otherwise. U.S. citizenship is a U.S. citizenship indicator that takes on 1 if a person holds U.S. citizenship, either native or naturalized, and takes on 0 otherwise.

[10] Those who answered that their education is closely related to their job are categorized into 3 educational groups (bachelor, master, doctor). Those who answered that their education is not related to their job at all are also categorized into 3 educational groups (bachelor, master, doctor). Those who answered that their education is somewhat related to their job are considered to be one group. There are 7 cells in terms of education–job relation.

we found for non–EJR self–employed indicates a possibility of non–pecuniary motives. Our probit estimation reveals that, for both categories, the relative monetary returns are a major determinant of being self–employed. We can now summarize our estimation results as follows.

Evidence 3

For highly–educated individuals in our sample, pecuniary returns are a primary motive for being self–employed as well as for being paid employees.

This evidence is in line with our model, but the non–monetary compensation hypothesis is not supported by our structural probit analysis. This evidence should be however treated with caution. As Heckman (1998) stresses, self–selection problems cannot be completely resolved unless we have an exogenous variation in an endogenous variable. Unfortunately, we do not have such a variable, usually coming from a natural experiment, in our data set. Therefore, we are not able to rule out a possibility that we obtained Evidence 3 because we failed to adequately control for self–selection biases.

3.3.3 An Evaluation Based on Estimated Earnings Differentials from Counterfactual Setting

In this section we reexamine earnings differentials between self–employed and paid employees by employing the counterfactual setting described in the previous section. Since a person is either self-employed or a paid worker in our setting, we can express observable log earnings, $\ln y$, as

$$\ln y = \mu^P + x\beta^P + D\left[\left(\mu^S - \mu^P\right) + x\left(\beta^S - \beta^P\right)\right] + \epsilon$$

where $\ln y = D \ln y^S + (1 - D)\ln y^P$ and $\epsilon = v^P + D\left(v^S - v^P\right)$. Our estimating equation now can be written as

$$\ln y = \delta_1 + x\delta_2 + D\alpha + D\left(x - \overline{x}\right)\delta_3 + \epsilon \tag{21}$$

where $\overline{x} = E(x)$. Our parameter of interest is α of the self–employment status dummy variable since we have

$$E\left(\ln y^S - \ln y^P\right) = \alpha \tag{22}$$

after accounting for endogeniety problems. Parameter α captures effects of self–employment status on earnings for a person randomly chosen from a target population. The non–monetary hypothesis predicts that an estimate of α should be negative while our model expects the estimate of this coefficient to be zero.

Table 6 shows estimation results for the coefficient of self–employment status, α, by using three different estimation methods. For the OLS regression, we treat unobserved terms v^S and v^P as identical and do not try to account for potential selectivity biases while the first difference regression tries to correct potential endogeneity problems arising from individual's fixed effects by using repeated observations. Selection corrected regression allows v^S and v^P to be different and uses selectivity bias correction terms appearing in equations (18) and (19) when estimating the earnings differential.

[Table 6 here]

Since the OLS estimation method is similar to the Hamilton's method we employed in Section 3.2, it produces qualitatively the same results: The expected earnings differentials are positive for EJR self–employed and negative for non–EJR self–employed. As mentioned above, this estimation result does not give us much information since potential endogeneity problems are not taken into consideration. Panel B of Table 6 reports estimation results from the fixed effects model and shows that the earnings differential is not statistically significant for EJR self–employed while it is negative and statistically different from zero for non–EJR self–employed. As in Panel C of Table 6, the negative earnings differential for non–EJR self–employed is also found by another methodology that attempts to account for potential endogeneity problems. We can summarize our results as

Evidence 4

The estimated earnings differential under the counterfactual setting is non–negative for EJR category but it is negative for non–EJR category.

Our model does not provide any explanation for this evidence, but this evidence is in line with the non–monetary compensation hypothesis. Thus, the non–monetary compensation hypothesis may be able to explain partially for behaviors of non–EJR category of self–employed, although it cannot explain EJR category of self–employed well.

4 Concluding Remarks

This study examined whether monetary or non–monetary motives play a significant role in entrepreneurship by examining highly–educated self–employed in science and enigneering fields. Our overall analysis suggests that self–employment activities are explained largely by the model where relative monetary returns to self–employment are a key determinant for one's decision on self–employment status as well as for earnings differentials. Several interesting insights presented in this study were obtained by disaggregating self–employed into two groups according to a level of human capital. In contrast to past studies, this split allowed us to find that not all self-employed just enjoy non-pecuniary returns. This is one of the most important messages in this study.

When our theoretical and empirical analyses are combined, this study also suggests that highly-educated self-employed in the science and engineering workforce are not rewarded for higher education per se, but they are rewarded for capability to understand and implement advanced technical knowledge. Even among highly educated self-employed, not all self-employed seem to posses this entrepreneurial ability and perform such an entrepreneurial function. Thus, it is not appropriate to blindly extend our conclusions here to any type of independent business owners. For example, it would be natural to expect that owners of corner stores or educationally disadvantaged self-employed are unlikely to perform entrepreneurial functions that require advanced technical knowledge. These self-employed likely perform different nature of entrepreneurial activities, and their behaviors may be explained well by other theories of entrepreneurship offered by past empirical studies mentioned above. It is worthwhile to emphasize that we reach our main conclusion from a systematic examination of a large body of data on scientists and engineers educated and working in the United States, not from a particular case study.

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Tables

Table 1: Summary Statistics

	self-employed		paid workers	
	Number	**Fraction**	**Number**	**Fraction**
Gender				
male	6,570	0.758	96,124	0.727
female	2,092	0.242	36,160	0.273
Race				
white	7,013	0.810	96,396	0.729
non-white	1,649	0.190	35,888	0.271
Highest educational degree				
bachelor	3,676	0.424	55,953	0.423
master	1,991	0.230	32,744	0.248
doctor	2,995	0.346	43,587	0.329
Job relation to educational degree				
closely related	4,027	0.465	70,948	0.536
somewhat related	2,259	0.261	41,310	0.312
not at all	2,376	0.274	20,026	0.151
Average age	46.41		40.31	

Source: authors' estimation, using restricted-SESTAT data for 1995, 1997, 1999.

Table 2: Summary Statistics on Annualized Income

A. all					
	mean	**std**	**percentiles**		
			25th	**50th**	**75th**
self-employed	63,945	52,221	32,500	54,143	82,857
paid workers	57,058	34,017	36,190	52,381	71,429

B. job relation to education					
	mean	**std**	**percentiles**		
			25th	**50th**	**75th**
	closely related				
self-employed	73,316	56,450	41,905	62,000	91,743
paid workers	58,462	32,458	38,532	55,000	71,619
	somewhat related				
self-employed	61,891	44,881	32,000	50,000	81,651
paid workers	59,555	36,119	38,095	55,000	73,394
	not at all				
self-employed	50,015	47,759	22,936	38,095	64,220
paid workers	46,934	33,135	25,000	40,000	60,000

Source: authors' estimation, using restricted-SESTAT data for 1995, 1997, 1999.

Table 3: Estimations of Earnings Equations for Self and Paid Employed Workers

	(I)				(II)			
explanatory variables	self-employed		paid workers		self-employed		paid workers	
master's degree holder	0.05162	**	0.12133	**	0.05280	*	0.11653	**
	(0.02437)		(0.00336)		(0.03157)		(0.00496)	
doctorate degree holder	0.24962	**	0.35289	**	0.20821	**	0.34957	**
	(0.02665)		(0.00362)		(0.03278)		(0.00487)	
education-job-relation (EJR)	0.20136	**	0.03820	**	0.16664	**	0.03365	**
	(0.02350)		(0.00283)		(0.03358)		(0.00427)	
master x EJR					0.01241		0.00902	
					(0.04932)		(0.00666)	
doctor x EJR					0.10301	**	0.00673	
					(0.04951)		(0.00629)	
labor experience	0.01232	**	0.03672	**	0.01267	**	0.03674	**
	(0.00443)		(0.00054)		(0.00443)		(0.00054)	
labor experience squared	-0.00032	**	-0.00069	**	-0.00033	**	-0.00069	**
	(0.00010)		(0.00001)		(0.00010)		(0.00001)	
tenure	0.02430	**	0.01059	**	0.02428	**	0.01058	**
	(0.00366)		(0.00056)		(0.00366)		(0.00056)	
tenure squared	-0.00047	**	-0.00012	**	-0.00048	**	-0.00012	**
	(0.00014)		(0.00002)		(0.00014)		(0.00002)	
gender	0.23148	**	0.11175	**	0.23015	**	0.11173	**
	(0.02317)		(0.00311)		(0.02317)		(0.00311)	
white	0.01958		0.05523	**	0.02096		0.05529	**
	(0.02352)		(0.00294)		(0.02352)		(0.00294)	
marriage	0.12042	**	0.07007	**	0.12095	**	0.07007	**
	(0.02187)		(0.00304)		(0.02188)		(0.00304)	
constant	10.36436	**	10.17706	**	10.37386	**	10.17912	**
	(0.06268)		(0.00655)		(0.06307)		(0.00671)	

Source: authors' estimation, using restricted-SESTAT data for 1995, 1997, 1999.

Note: (i) The dependent variable is logarithm of annualized income. (ii) The number of observations used is 140,946. Of the total number, 8,662 pertain to self-employed individuals, while 132,284 observations are on paid employees. (iii) Estimates of coefficients of occupational dummies are suppressed. (iv) Numbers in the parentheses are standard errors. (v) ** and * indicate that coefficients are significant at 5 percent level and at 10 percent level, respectively.

Table 4: Estimations of Percentage Entrepreneurship Premia

point of measurement	full sample	EJR	non-EJR
A. 0 year of prior labor experience			
mean	3.5	25.3	-10.8
25th	-10.2	6.8	-23.8
median	4.1	24.6	-10.6
75th	27.1	52.7	8.9
B. 5 years of prior labor experience			
point of measurement	full sample	EJR	non-EJR
mean	-0.6	18.0	-13.0
25th	-13.1	3.5	-25.0
median	0.7	19.2	-12.3
75th	23.0	44.1	7.4
C. 10 years of prior labor experience			
point of measurement	full sample	EJR	non-EJR
mean	-4.3	11.8	-15.2
25th	-15.8	0.4	-26.4
median	-2.3	14.2	-13.9
75th	18.8	36.1	6.0
D. 15 years of prior labor experience			
point of measurement	full sample	EJR	non-EJR
mean	-7.7	6.5	-17.2
25th	-18.4	-0.2	-27.7
median	-5.2	9.5	-15.3
75th	14.7	28.6	4.5

Source: authors' estimation, using restricted-SESTAT data for 1995, 1997, 1999.

Note: (i) Numbers in tables are an estimated percentage entrepreneurship premium. (ii) The number of observations for the full sample is 140,946. The number of observations for EJR category is 74,975 while the number of observations for non-EJR category is 65,971.

Table 5: Estimation from Structural Probit Model

variable	(I)		(II)		(III)		EJR		non-EJR	
predicted earnings difference	0.0760	**	0.1310	**	0.1488	**	0.1183	**	0.2274	**
	(0.0033)		(0.0033)		(0.0033)		(0.0037)		(0.0043)	
certification	0.0127	**	0.0288	**	0.0331	**	0.0515	**	0.0412	**
	(0.0007)		(0.0011)		(0.0012)		(0.0019)		(0.0025)	
U.S. citizenship	-0.0043	**	-0.0100	**	-0.0118	**	-0.0118	**	-0.0115	**
	(0.0002)		(0.0004)		(0.0004)		(0.0005)		(0.0014)	

Source: authors' estimation, using restricted-SESTAT data for 1995, 1997, 1999.

Note: (i) Numbers in tables are estimated marginal effects on being self-employed rather than paid employees. (ii) Numbers in the parentheses are robust standard errors. (iii) ** and * indicate that coefficients are significant at 5 percent level and at 10 percent level, respectively.

Table 6: Estimations of Earnings Differentials under Counterfactual Setting

variable	full sample		EJR		non-EJR	
	A. OLS regression					
self employment	-0.01504		0.08043	**	-0.10502	**
	(0.01401)		(0.02111)		(0.01955)	
	B. first difference regression					
self employment	-0.03056	*	-0.00921		-0.04993	**
	(0.01748)		(0.02576)		(0.02335)	
	C. selection corrected regression					
self employment	-0.05422	**	0.04786	**	-0.12923	**
	(0.01449)		(0.02145)		(0.02069)	

Source: authors' estimation, using restricted-SESTAT data for 1995, 1997, 1999.

Note: (i) The dependent variable is logarithm of annualized incom. (ii) OLS and first difference regressions use a two-year panel data. The number of observations used in these regressions is 48,331 for the full sample. The number of observations for EJR category is 25,986 while the number of observations for non-EJR category is 22,345. Selection corrected regression uses the cross-sectional data. (iii) Numbers in the parentheses are robust standard errors. (v) ** and * indicate that coefficients are significant at 5 percent level and at 10 percent level, respectively.