

**The Role of Schooling in Taiwan's Labor Market:
Human Capital, Screening or Credentialism?**

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ABSTRACT

A classic issue in social stratification is whether the correlation between an individual's education and his or her socioeconomic attainment is derived from increased productivity (i.e., human capital), labor market screening or simply from his or her credentials (credentialism). All three theories predict an association between education and socioeconomic status, but they differ with regard to the precise underlying causes of such a relationship. While previous research has largely avoided the challenge of empirically testing these three competing explanations, here we provide some relevant findings to tackle this research dilemma. More specifically, we investigate the effects of different measures of schooling on productivity so as to provide systematic evidence that is pertinent to distinguishing between the different perspectives in an empirical manner. The results of our analysis of recent data on productivity and schooling in Taiwanese manufacturing industries clearly support the view of education as productive human capital and provide limited backing for the notion of a mechanism for labor market screening. Since these results only pertain to the manufacturing sector, they cannot be used to generalize about the entire economy. Nonetheless, we conclude that our findings demonstrate that this difficult research problem can indeed be empirically investigated and that, in the future, researchers should consider revisiting the challenge of understanding the nature of the various effects of education on social stratification.

Key words: human capital, screening, credentialism, labor productivity

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I. Introduction

A well known fact is that schooling is closely associated with greater socioeconomic status, and not surprisingly, this correlation has been noted across various units of analysis. Workers who have more schooling, for one, tend to have higher wages (Card 1998) and more rewarding occupations (Featherman and Hauser 1978). Along the same line, American metropolitan areas and states with more highly educated residents report higher average incomes (Chiswick 1974; Hale and Main 1977; Hirsch 1978). As for industries, those with more educated workers evidently have greater productivity (Galle et al. 1985) and earnings (Dickens and Katz 1987; Hirsch 1982), a fact which has long led economists to argue that educational expansion has significantly contributed to economic growth (Jorgenson 1984; Jorgenson and Fraumeni 1995a); the analysis of Walters and Rubinson (1983) suggests, however, that these effects may have been somewhat more disparate during the first part of the twentieth century. But, economic factors aside, even the prestige rankings of occupational titles are greater for workers with higher levels of schooling (Duncan 1961). In short, the positive associations between schooling and socioeconomic status generally go undisputed and can, indeed, be observed in different units of analysis.

Although this association between schooling and socioeconomic status is widely observed in a variety of contexts, considerable disagreement still exists when it comes to the precise causal nature of this association. In this paper, we seek to clarify some of the substantive differences among these theoretical disagreements. Specifically, we investigate the effects of different measures of schooling on productivity and provide systematic evidence to empirically draw distinctions between the three different perspectives.

Given this objective, we organize the theoretical perspectives into three basic views: (1) the technical-functional view; (2) the market-signal view; and (3) the credentialism view. In the following, we summarize these three perspectives and derive testable hypotheses which seek to disentangle their substantive differences. We then present our

empirical results regarding these hypotheses and discuss their implications.

II. Theoretical Background

The Technical-Functional View

According to the technical-functional view (Collins 1971), education directly augments economic productivity, not to mention the potential of workers; workers with more education are inclined to be more productive on account of their schooling experiences. This view recognizes that while there are also other sources of worker productivity, education is very important in providing workers with the crucial components of the training and skills required for competency in more complex jobs. As noted by Collins (1971, p. 1004) in his discussion of the assumptions of the technical-functional view, "...formal education provides the training, either in specific skills or in general capacities, necessary for more highly skilled jobs."

More specifically, based on this theory, education improves an individual's productivity in several ways. First, education increases a person's cognitive skills, such as in mathematics and writing. Second, education normally provides training in work skills by increasing one's familiarity and facility with the technology involved in production, such as that with machines, materials, computers or technical instruments. Third, education can increase an individual's productivity by conditioning important social skills, like the ability to communicate, to work with others and to be reliable and disciplined.

According to Collins (1971, p. 1004), the technical-functional view can be interpreted as being consistent with the general functional theory of social stratification as discussed by Davis and Moore (1945). In brief, this functional theory states that education provides substantial components of the greater skills and training that are required for the competent performance of more complex jobs. In order to motivate people to endure the various costs and bother of completing additional schooling and training, jobs which are more complex and more important (or at least their higher demand in the economy) seemingly offer greater socioeconomic rewards. Given this, higher rewards for more complex jobs have now become accepted as legitimate and necessary.

An economic version of the technical-functional view is the human capital theory (Becker 1975; Rubinson and Browne 1994), and the assumptions discussed above are generally applicable here, as well. The major additional theoretical elements in the human capital theory, as typically espoused by economists, are the general presumptions that labor markets are highly competitive in the same way that product markets are and that differences in workers' productivities (which reflect their varying amounts and stocks of human capital) are the driving forces underlying differences in wages (Sorensen and Kalleberg 1981). Common to both the sociological technical-functional view and the economists' human capital theory, however, is the fundamental idea that education directly augments the individual's productive capacities; education, in other words, enhances productive human capital.

One important implication of this concept is that a *prima facie* general solution to the problem of poverty and inequality exists, and that is that increases in the education of the poor and of the working-class will correspondingly bring about increases in their incomes (Aaron 1978, pp. 70-71; Bluestone 1977, p. 337; Schiller 1984, p. 117; Sorensen and Kalleberg 1981, p. 69). To state this in a more general way, and as discussed by Becker (1975, p. 86), a reduction in the inequality in the distribution of schooling will lessen the degree of inequality in the distribution of wages.

The Market-Signal View

According to the market-signal view, education certifies which people have greater ability and trainability but, in what may seem paradoxical, schooling does not significantly reinforce those traits in any direct way. The main value of education *per se* is to serve as a signal in a labor market where information about a person's abilities is highly imperfect. Education is typically correlated with a person's productivity and thus with his or her socioeconomic attainment, but as a rule, education *per se* does not directly enhance the economic productivity of a firm (Thurow 1975).

A major assumption in the market-signal view--which clearly differentiates it from the technical-functional view--is that most work skills are learned on the job and in the workplace rather than in school. That is, students do not learn very much in school that actually enhances their economic performance. Actual work skills are said to be too far

removed from the activities that come with schooling. Instead, work skills are developed through job experience and the on-the-job training that is informally provided by senior workers (Sorensen and Kalleberg 1981; Thurow 1975).

However, education is still valued by employers because it serves as a valid signal or certification of the extent to which an individual has discipline, trainability and a general capacity to learn. As noted by Thurow (1975, p. 88), these are all important traits that employers value in workers because of the salient role of on-the-job training in the development of work skills. Thus, an individual's education is a market-signal that provides strong *prima facie* evidence to an employer that s/he can readily be trained to become a more productive worker (Spence 1981).

Simply put, in accordance with the market-signal view, education is associated with productivity, but it does not directly cause it.¹ The association arises because people with more education tend to have more of those traits that make a person economically productive--discipline, trainability and ability--but those traits are not significantly enhanced by education. Thus, the bivariate association between education and economic productivity is said to be spurious: their association stems from a common cause (i.e., the individual's discipline, trainability and other productive traits).

The market-signal view, for the most part, also assumes that a worker's productive traits and capacities are often difficult to directly assess. This, therefore, reinforces the reliance upon education as a market-signal or certifying device. This may simply reflect the fact that information about workers' abilities, trainability and potential productivity are just too difficult to accurately ascertain, measure or observe. These problems of assessment or evaluation may especially be pronounced in firms where the production process is highly interdependent and is characterized by non-constant returns to scale, or when senior workers are crucial in providing training to junior workers (Thurow 1975).

Another typical presupposition of the market-signal view is that the labor market consists of a set of job slots that firms seek to fill with people who pose the least risk of necessitating higher training costs--that is, with people who will quickly learn to do the

¹ One strand of research in the human capital tradition which may implicitly recognize some role for the market-signal value of schooling is the economic research on "ability bias" in the estimation of the returns to schooling. Recent studies using sibling data, however, do not seem to yield estimates that are substantially less than those obtained using more conventional methods and data sets (Ashenfelter and Kreuger 1994; Ashenfelter and Zimmerman 1997).

job well (Thurow 1975). One important implication of this assumption, in the context of the market-signal view, is that in determining the socioeconomic status of a job, a person's relative educational attainment is more important than his or her absolute educational attainment because relative educational attainment actually determines his or her place in the labor queue.² In other words, although education is the primary screening device that employers value most in that it most accurately certifies who requires lower training costs, "it is a person's relative position in the distribution of education that counts"(Sorensen and Kalleberg 1981, p. 69).

Worth noting too is that, in contrast to the technical-functional view, the market-signal view does not predict that the distribution of wages is much affected by changes in the distribution of education (Sorensen and Kalleberg 1981, p. 69). With regard to the problem of eliminating poverty wages in the distribution, Levin (1977, p. 168) observes that "in a way, we are describing a game of musical chairs" because the fundamental problem of not having enough good-paying jobs is not substantially affected by the distribution of education from the market-signal viewpoint. This means that changing the distribution of education will likely change who gets the better jobs but the poverty rate for the economy will not be significantly reduced because "there are still fewer chairs than there are people" (Levin 1977, p. 168). In sum, the market-signal view of education is not optimistic vis-à-vis the notion that education can do a lot to reduce poverty or equalize the distribution of wages because the key assumption is that education is only a certifying device that does not directly contribute to economic productivity.

The Credentialism View

The credentialism view is related to the market-signal view in that both share the assumption that what students learn in school does not actually improve their economic performance in the workplace very much. While both approaches agree that education does not directly augment one's productivity (at least not significantly), the credentialism view differs from the market-signal view since it goes one step further by claiming that

² Sakamoto and Powers (1995) tested this hypothesis with regard to obtaining employment in the corporate sector of the Japanese economy.

education is not even correlated with productive abilities or capacities, let alone overall productivity (Collins 1979).

According to the credentialist view, the reason for the association between education and socioeconomic attainment is not due to any relationship with economic productivity; on the contrary, it is a result of class conflict. This perspective is not unlike the theory imbedded in discussions on cultural capital. As Farkas (1996) suggests, a key feature of the conflict synthesis is the theory of cultural capital, which builds with its own status culture controlling access to the rewards and privileges of group membership. In other words, cultural capital, along with economic, social and symbolic capital, serves as a power resource or a way for groups to either remain dominant or gain status. Also as stated by Burris (1983, p.465), “Employers rely on educational credentials in hiring and promoting not because of the technical skills these represent, but as a means of selecting people who are socialized into the dominant status culture.” In general, the credentialist view maintains that education serves to legitimize and reinforce inequality in the labor market both in terms of authoritative relations and the distribution of wages (Bowles and Gintis 1976). Jobs which pay higher wages to more educated workers do so not because those workers are actually more productive but because their higher education has established them as being a member of a morally superior status group that deserves to not only be in power but also enjoy greater rewards (Berg 1970; Bourdieu 1977; Collins 1971, 1979).

An additional reason for the association between education and socioeconomic attainment, according to the credentialist view, is that education serves the interests of dominant social classes as far as the intergenerational transmission of inequality goes. That is, education is a mechanism by which higher status groups can reinforce and pass on some of their higher status to their offspring. Owing to inequalities with regard to educational opportunities--needless to say, in favor of the wealthy and powerful--the dominant social classes are able to ensure that their children are much more likely to obtain a high level of educational attainment. The association between education and socioeconomic rewards, therefore, helps to promote the intergenerational perpetuation of inequality (Bowles and Gintis 1976).

III. Schooling, Economic Productivity and Units of Analysis

The distinctions among the aforementioned three perspectives could certainly be discussed at greater length, but for the purposes here, we contend that the most critical substantive difference among them is that they differ with respect to the predictions they make about the relationship between schooling and productivity. To be more specific, according to the technical-functional view, an increase in schooling should directly result in greater productivity because education is deemed to represent human capital.

On the other hand, the credentialism view predicts that an increase in schooling does not increase productivity because the educational system serves to perpetuate class inequality and exploitation; the observed association between education and socioeconomic status is simply symptomatic of the fundamental economic irrationality of capitalism. The intermediate position here is represented by the market-signal view which predicts that firms which hire workers with more schooling should indirectly increase productivity because such workers have lower training costs and are more disciplined (although, in contrast to the technical-functional view, these latter qualities do not derive from their schooling *per se*).

Although quantitative sociological studies of productivity are rare (Galle et al. 1985; Tomaskovic-Devey 1988; Walters and Rubinson 1983), there is no reason that they cannot be a fruitful area of sociological inquiry, particularly when they involve such important substantive issues as the understanding of the causal relationship(s) between schooling and socioeconomic status. While one might argue that, for an analysis of productivity and schooling, the individual is the most desirable unit of analysis (Rubinson and Browne 1994, pp. 583-584), objectively-defined productivity statistics are not available for a broad representative sample of workers.³ In the modern economy, whole products are usually not produced separately by individuals. For this reason, only for a limited number of jobs, e.g., in some sales occupations and some blue-collar jobs, can output be directly measured in objective economic terms at the individual-level (Sorensen 1994, pp. 515-518). Therefore, if one insists (as apparently Rubinson and Browne 1994 do) that productivity must be measured at the individual level, then a systematic

³ This absence is reflected, for example, in Petersen (1992) who used a worker's wage as an indicator of his or her productivity.

sociological analysis of productivity is hardly possible.

We argue, however, that an aggregate unit of analysis is appropriate for the investigation of our underlying theoretical questions. Each of the three theoretical perspectives discussed above implies a corresponding aggregate-level relationship between productivity and schooling. From the standpoint of the technical-functional approach, workers who have more schooling should have developed more human capital. At the level of the firm, productivity is greater (*ceteris paribus*) if its workers have a higher average level of human capital. We believe that this aggregate relationship is indeed the essential logic motivating the use of the term “human capital.” In any event, the argument that an aggregate measure of human capital increases productivity measured at some aggregate unit is well formulated in the literature in the field of economics and represents some of the classic statements of human capital theory (Griliches 1970; Jorgenson and Fraumeni 1995a; Schultz 1961b).

From the point of view of the market-signal approach, the theoretical basis of an aggregate-level analysis is less well developed. We believe, however, that the essence of this perspective is the assumption that the primary role of schooling is to certify rather than directly augment the productivity of an individual; this assumption is fundamental because it clearly differentiates the market-signal approach from the technical-functional view.

According to the market-signal approach, employers value workers who are more highly certified because in fact such workers, by and large, do tend to be more productive and/or have lower training costs. However, because schooling does not directly augment productivity, the total years of schooling *per se* is not the most appropriate indicator of a person’s level of certification. Rather, greater relative educational attainment is the relevant measure because, in contrast to the technical-functional view, schooling *per se* is irrelevant to economic productivity; the value of the signal derives from a person’s relative standing on the ladder of educational competitiveness because his or her relative standing reveals his or her productive potential.⁴

Because schooling is a signal or certification of an individual’s productivity or

⁴ This type of competition has a tendency to develop a rat-race quality since the “growth in education will feed itself as more and more education is needed to secure the same relative position” (Sorensen and Kalleberg 1981, p.69).

trainability, the output of a firm should be greater (*ceteris paribus*) to the extent that its workers have higher relative educational attainment (i.e., are more highly certified or are providing a stronger signal) than do those of other firms. Thus, at the level of the firm, the market-signal view does imply that a more highly educated workforce contributes to increased productivity, but in contrast to the human capital approach, the appropriate measure for the market-signal view is a higher level of relative educational attainment rather than the mean number of years of schooling *per se* (although the latter measure is often used in human capital studies of economic productivity).

As for the credentialism view, the essence of the concept of a credential (at least as used in this literature) is that it helps sustain class inequality rather than economic efficiency or productivity. In other words, the fundamental assumption here is that schooling does not specifically relate to economic productivity; schooling is hypothesized to be uncorrelated with productivity. The implication of this line of reasoning with respect to the level of a firm is that the economic output of firms with more highly educated workers is not necessarily greater than that of firms with less educated workers (*ceteris paribus*). Because an individual worker is no more productive for having gone to school longer, it seems reasonable to infer that firms are no more productive (*ceteris paribus*) for having hired a more educated workforce. They may be more accepting of the social and economic inequality of the firm, but they are not regarded as being more economically productive.

In sum, these three theoretical perspectives give rise to different predictions regarding the relationship between firm-level productivity and the schooling characteristics of the workforce. And, these different predictions can be assessed with empirical data. Nonetheless, the interpretations derived from these theories are not necessarily self-contradictory or mutually exclusive. Recent studies have also drawn some different conclusions on account of the differences in the data or methodology. For example, Chang et al. (1996) emphasize the value of credentials and argue that it is already conventional wisdom in Taiwan that an individual with a higher level of educational attainment will enjoy increased opportunities for greater socioeconomic achievement. Yu and Chu (1998) find, however, that the performance of graduates from the most prestigious university (i.e., National Taiwan University) in terms of salary and

employment is not significantly superior to that of graduates from other colleges in Taiwan. Based on their thorough data analyses, Tsay and Lin (2000) underscore the importance of a firm's first position rather than other factors. Liu and Li (2001) conclude that a worker's credentials are useful for entering the labor market but have little effect on his or her future career development. Because of this, it is important and interesting to carry out some sort of quantitative social accounting of the relative strength of each theory. In the following, we discuss this issue in greater detail.

IV. Operationalizing Hypotheses about Schooling and Productivity

There are no publicly available data sets that contain data on the productivity of particular firms along with information on the schooling of their workforce. In lieu of firm-level data, we therefore use data on industries which represent groups of firms that produce similar products. Our data consist of two-digit manufacturing industries for which there is an established tradition of economic statistics and data collection on productivity.⁵

We use an objectively-defined measure of productivity, namely the dollar value of the output produced per employee-hour in the two-digit manufacturing industries. In order to provide a more methodologically conservative test of our theoretical concerns, we restrict our study to manufacturing industries because productivity data are more likely to be valid and reliable for the manufacturing sector than for others, such as services where the output is sometimes less directly measured or quantifiable.⁶

Restricting the analysis of productivity to one sector also reduces the number of complications that might arise from the high degree of technological heterogeneity across sectors. In our analysis, we estimate the net effects of measures of educational attainment on labor productivity using the two-digit manufacturing industry as the unit of analysis. To do so, our model is developed from the Cobb-Douglas production function which, in various formulations, is well known and widely used in economics (and is also used by Walters and Rubinson 1983):

⁵ We do agree that firm-level data would be very useful to have, and we are in the process of collecting such data (this research proposal has been approved by the NSC).

⁶ Galle et al. (1985, p.24) and Tomaskovic-Devey (1988, p.147) restricted their analyses to the manufacturing sector for the same reason.

$$Q = AK^\alpha L^\beta \quad (1)$$

where A is a constant reflecting the scaling of the measures; Q is the quantity produced during the given time period in which K units of capital are used and L units of labor are employed; and α and β are parameters to be estimated. In this simple model, the L units of labor are undifferentiated in terms of quality or human capital.

A human capital version of Equation (1)--that is, a formulation that would be more explicitly consistent with the technical-functional view--would in some fashion include measures of the educational attainment of workers involved in the production process. For example, Equation (1) could be extended by including the mean or median years of schooling completed by workers (Galle et al. 1985; Kendrick and Grossman 1980) or by including some composite index or other indicators of the distribution of years of schooling completed by workers (Griliches 1970; Jorgenson and Griliches 1995; Walters and Rubinson 1983). Because the human capital model assumes that workers who have completed more schooling are accordingly more productive, the inclusion of the measures of the extent of schooling completed by workers in Equation (1) operationalizes the hypothesis that states that increased educational attainment should increase productivity.

At the same time, Equation (1) can also be extended to test for the predictions of the market-signal view of education. According to this explanation of the role of education in the labor market, industries are more productive to the extent that they are able to attract workers who require lower training costs and/or have greater ability (e.g., Thurow 1975, p.121). Because the market-signal view assumes that education *per se* does not significantly increase productivity but is only correlated with workers' trainability which, in turn, lowers training costs, the mean level of schooling *per se* among workers does not significantly increase productivity.⁷ Instead, as noted by Thurow (1975, p.95), the market-signal view implies that the labor market clears or reaches equilibrium by adjusting hiring standards rather than wage rates; thus, we may predict that productivity will be greater in industries in which workers, generally speaking, have higher relative

⁷ Thus, according to the market-signal view of education, aggregate economic growth is not affected by increases in the total stock of educational human capital that is embodied in workers, but such an accumulation has been the subject of investigation among economists working within the theoretical framework of the human capital view (Denison 1962; Jorgenson 1984; Jorgenson and Fraumeni 1995).

educational attainment, as discussed earlier.

At the level of the individual worker, let s refer to his or her years of schooling and r to the percentile ranking associated with that number of years of schooling (where the percentiles are based on the distribution of years of schooling for all workers in the labor force). At the level of the industry, let S refer to the mean years of schooling completed by workers in a particular industry and R to the mean of the percentiles associated with the years of schooling completed by the workers employed in a particular industry. Thus, industries with a larger value of S are those in which the workers have, on average, spent more time in school, while industries with a larger value of R are those in which the workers have, on average, achieved a relatively higher level of educational attainment.

While s and r can be expected to be highly correlated, there is nonetheless a crucial difference between S and R . Across the labor force as a whole, the mean of S increases over time as the Taiwanese education system expands and the average levels of educational attainment increase. By contrast, the mean of R across the labor force as a whole cannot increase because, by construction, the mean for a distribution of percentiles is always approximately 50%. This latter feature is consistent with the fundamental assumption of the market-signal view which is that education serves to certify which people have greater ability and trainability and that schooling *per se* does not directly augment those traits significantly in ways that are pertinent to economic productivity.

S and R may be both included to Equation (1) to derive a model that can be estimated to test the relative predictive power of these theories of the role of education in the labor market:

$$Q = AK^\alpha L^\beta S^{\delta_s} R^{\delta_r} \quad (2)$$

Once Equation (2) is estimated with actual data, the two empirical results that would most strongly support the technical-functional (i.e., human capital) view of education would be: (1) reject $H_0 : \delta_s \leq 0$; and (2) fail to reject $H_0 : \delta_r \leq 0$. This set of results would underscore the importance of the absolute amount of education obtained by workers in influencing productivity and would, consequently, be consistent with the interpretation of education as representing stocks of human capital. Such results would also be contrary to the expectation of the market signal view which places a great deal of emphasis on relative educational attainment as an indicator of one's potential

productivity.

Empirical results that would support the market signal view would be: (1) fail to reject $H_0 : \delta_s \leq 0$; and (2) reject $H_0 : \delta_r \leq 0$. This set of results would indicate that the mean number of years of schooling *per se* has no net effect on productivity---that schooling does not really constitute productive human capital. However, education would still be important in explaining inter-industry variations in productivity because the finding that $\delta_r > 0$ implies that productivity is greater in those industries which employ workers who have a relatively higher educational attainment. In other words, the empirical results that would support the market signal view are exactly opposite those that would support the technical-functional view. Nonetheless, the human capital and market signal views are not necessarily mutually exclusive. It might be argued that if the empirical results rejected both $H_0 : \delta_s \leq 0$ and $H_0 : \delta_r \leq 0$, then both theories are supported, to some degree. The credentialism view can also be evaluated on the basis of the empirical results obtained from the estimations from Equation (2). Specifically, the credentialism view would be supported if the results indicated that we should fail to reject both $H_0 : \delta_s \leq 0$ and $H_0 : \delta_r \leq 0$ simultaneously. This result would support the credentialism view which assumes that productivity is uncorrelated with education in terms of either years completed or percentile rank. In this case, education is neither productive human capital nor an accurate market signal about a worker's productive capacities; educational attainment is simply irrelevant to economic productivity.

Sorensen's Educational Attainment Score (EDR)

As a further test of these hypotheses on the relationship between education and productivity, we also operationalize an additional version of Equation (2) in which Sorensen's (1979, p. 371) educational attainment score (*edr*) is used instead of *r* to indicate a worker's relative educational attainment. *edr* is a measure of relative educational attainment that Sorensen (1979) derives from his formal analysis of the effect of schooling on status attainment in the context of the job competition model. Because the market-signal view of education is often based on the job competition model of the labor market, we also estimate regressions based on *edr* in order to ascertain whether our

conclusions about the predictive power of the market-signal view are affected by the use of a potentially more appropriate metric.⁸

At the individual level, Sorensen's educational attainment score, *edr*, is simply a nonlinear transformation of the percentile ranking of one's years of schooling completed, *r*. In particular, at the individual level:

$$edr = 100*[-\ln(1 - r/100)] \quad (3)$$

Sorensen's (1979) essential rationale for this function is that the competitive advantage afforded by an increased percentile ranking is not uniformly distributed across all levels of percentiles. As stated by Sorensen (1979, p. 371), "If the ordinality of educational attainment measured in years of schooling was the only concern, percentiles might seem an appropriate metric....However, using percentiles implies that the underlying variable--competitive advantage--is uniformly distributed, which seems an unwarranted assumption."

As we mentioned earlier, the mean of *r* at the level of the industry is **R**. Also at the level of the industry, let **EDR** refer to the mean of *edr*. Note that *edr* is computed for each individual worker, and then the mean of *edr* is computed for each industry-time observation. Therefore, the natural logarithmic transformation of **R** would not equal **EDR**. We estimate our regressions using **EDR** in lieu of **R** in order to test the market-signal view against the technical-functional view. Although operationalizing Sorensen's (1979) particular model is not our research objective (and, in contrast to that paper, we do not seek to predict socioeconomic attainment for all individual workers), we do use Sorensen's (1979) metric in some of our analyses so as to provide further evidence regarding the robustness of our conclusions about the relationship between education and economic productivity.

In light of our discussion above, the predictions of the net effects of our schooling measures, which are derived from the three theoretical perspectives on labor productivity, are summarized in Table 1, and the empirical findings can be tested by one-tailed t-tests. For human capital theory, the net effect of years of schooling on productivity is expected to be significantly positive (via a one-tailed t-test), while that of rank in educational

⁸ Sorensen (1979) used the term "vacancy competition," but his model is actually very similar to Thurow's (1975) "job competition" model especially with regard to our primary theoretical concern which is the nature of the relationship between education and socioeconomic attainment.

attainment is not expected to be significant; as for the screening hypothesis, the expected effects of the schooling measures are just the opposite of those of human capital theory; for credentialism, none of our schooling measures are expected to be significant.

Table 1: Net Effects on Labor Productivity: Predictions from Three Theoretical Perspectives

Theory	Schooling Measures		
	Years of Schooling (S)	Percentile Ranking of Schooling (R)	Sorensen's Educational Attainment Score (EDR)
Human Capital Theory	<i>Significantly positive</i>	<i>Not significant</i>	<i>Not significant</i>
Screening Hypothesis	<i>Not significant</i>	<i>Significantly positive</i>	<i>Significantly positive</i>
Credentialism	<i>Not significant</i>	<i>Not significant</i>	<i>Not significant</i>

It should be noted that these expectations are theoretical: the human capital theory and the market-signal view are not necessarily mutually exclusive. General discussions of the role of education in the labor market also sometimes lump together the market-signal view and the credentialism view (Boylan 1993; Meyer 1977). It might be suggested that, to some degree and in some ways, all three of these theories are true. That is, it could be argued that these theories should be integrated into a broader, more comprehensive theory which stipulates that each one plays some role in explaining labor market outcomes for different types of workers or for the same workers at different points in their work careers. We would definitely welcome the delineation of such a theory, and we believe that our efforts here represent the first contribution ever made in this direction.

V. Data and Methods

The 1979, 82, 85, 89, 92, 95 and 98 *Taiwan Industrial Production Statistics Yearly Report* are used to obtain the indexes of industrial productivity (output per employee-hour). Because these indexes are calculated from the net value of different base years, we apply the 1991 *Taiwan Wholesale Price Index* to adjust these statistics into raw New Taiwan dollars. In addition, we use *The Report on Taiwan Factory Census* to

get the annual capital input for each industry. The *Monthly Bulletin of Earnings and Productivity Statistics* and the *Monthly Statistics of the Republic of China* provide monthly information on employees and their average working hours by industry. In general, data on annual Taiwanese labor productivity for the past 20 years are available for 2-digit industries which were coded by the Taiwan Standard Industry Classification Codes (the list of Taiwan manufacturing industrial categories is shown in Appendix 1). The individual-level data sets used are the *Taiwan Manpower Utilization Survey* for the 7 years stated above. These surveys contain information we need for this research: workers' demographic characteristics, hours worked, educational level, industry, occupation, establishment size, firm tenure, and so on.

In order to transform Equation (2) into an additive linear model that can be estimated by the least squares, we take the natural logarithm of both sides of the equation. In our particular application, we have annual productivity data for each of the 20 different manufacturing industries (i.e., $j = 1, 2, 3, \dots, 20$) for each of the 7 years (which are indicated by the subscript t). The dependent variable for the statistical model is $\ln Q_{jt}$ which refers to the log of the 1991 Taiwanese dollar value of output per employee-hour in the j th industry in the t th year. Because we use data pertaining to productivity per employee-hour, we do not need to control for the number of hours worked in the industry. To control for variations in capital utilization across industries and across time, we are able to include the value of annual capital expenditures per worker (in constant 1991 Taiwanese dollars) in the j th industry in the t th year in the statistical model. We also include the square of this variable.

Because our data cover a 20- year period, it should be kept in mind that the net effect of education on productivity might change over time due to economic development. Although the issue related to the association between educational expansion and economic growth has long been of interest to economists, no general consensus has been reached. Rubinson and Browne (1994) argue that education may simply allocate people within a relatively fixed distribution of jobs and that since education *per se* may not create more productive jobs, it does not necessarily have any effect on economic growth. Hwang's (1998) empirical results, in fact, indicate that educational expansion in Taiwan did not improve economic development. On the contrary, educational expansion was

the result of economic development (also see the review by Liu and Li 2001). In order to control for period effects, we include two dummy variables: one for the 1980's and the other for the 1990's (so that 1979 serves as the reference time period). The rationale for these dummy variables is to control for period changes in the business environment that affect industrial productivity in Taiwan.⁹

We estimate a fixed-effects regression model of labor productivity observed in these manufacturing industries across this time period. We use the least-squares dummy variable formulation of this model in which $J - I$ dummy variables are included to indicate the J units (Greene 2000, pp. 560-562) which in our application refers to the 20 industries. The rationale for this approach is that each industry may have unique aspects of technology that may influence its productivity but which are not fully reflected in the value of annual capital expenditures per worker. The fixed-effects specification also eliminates the problem of auto-correlated error terms across the years for each of the industries.

We estimate the models by the weighted least squares in order to correct for heteroscedasticity which was evident from residual plots. The weight that we use is the square root of the sample size for the j th industry in the t th year. The use of this weight is common in the least-squares estimation of regression models for which the data are aggregate statistics based on varying sample sizes (Johnston 1984, pp. 293-296). The residuals obtained from our weighted least squares estimation appear to be satisfactorily homoscedastic.

VI. Empirical Results

Descriptive Statistics

The descriptive statistics can be visually appreciated in Table 2. Because we have 7 years of data for 20 industries, the total sample size is 140. Across these 140 observations, the mean of the output per employee-hour is 486.39 New Taiwan dollars (in constant 1991 New Taiwan dollars), while the mean of the log of this variable is 5.39.

⁹ Period effects may derive from changes in Taiwan's infrastructure, taxes and industrial regulations. Our research design, however, is a simple version of the screening model because it assumes that the signal is constant across the workers' career, but this issue is partly addressed by breaking down the workers by cohort.

The mean of the annual capital expenditures per worker is 14,925.53 New Taiwan dollars (in constant 1991 New Taiwan dollars), while the mean of the log of this variable is 9.01.

Table 2: Descriptive Statistics (N = 140)

	Mean	S.D.	Max.	Min.
Hourly Output per Worker	486.39	953.61	5745.29	49.75
Log of Hourly per Worker	5.39	1.04	8.66	3.91
Capital Expenditures per Worker	14925.53	21783.90	126054.23	658.30
Log of Cap. Expend. per Worker	9.01	1.04	11.75	6.49
Log of Cap. Expend. per Worker Squared	82.29	19.28	137.94	42.12
Mean Years of Firm Tenure	5.85	2.57	20.01	2.62
Log of Mean Years of Firm Tenure	1.70	0.36	3.00	0.96
Mean Years of Schooling	9.54	1.36	13.14	6.67
Log of Mean Years of Schooling	2.25	0.14	2.58	1.90
Rank of Schooling by Total Labor Force	40.73	11.22	93.30	24.25
Log of Rank of Sch. by Total Labor Force	3.67	0.26	4.54	3.19
Rank of Schooling by 5-year Age Cohort	38.10	11.99	86.00	21.60
Log of Rank of Sch. by 5-year Age Cohort	3.60	0.29	4.45	3.07
Rank of Schooling by Gender	40.12	10.92	90.40	22.44
Log of Rank of Schooling by Gender	3.66	0.26	4.50	3.11
Rank of Schooling by Age and Gender	36.89	11.50	84.00	20.14
Log of Rank of Schooling by Age and Gender	3.57	0.29	4.43	3.00
EDR of Schooling by Total Labor Force	77.51	27.70	170.31	38.40
Log of EDR of Sch. by Total Labor Force	4.29	0.34	2.51	3.65
EDR of Schooling by 5-year Age Cohort	71.74	26.34	175.66	35.00
Log of EDR of Sch. by 5-year Age Cohort	4.21	0.35	5.17	3.56
EDR of Schooling by Gender	75.63	25.97	135.87	35.66
Log of EDR of Schooling by Gender	4.27	0.33	4.91	3.57
EDR of Schooling by Age and Gender	68.91	24.38	148.19	33.02
Log of EDR of Schooling by Age and Gender	4.17	0.34	5.00	3.50
Dummy Variable for 1982, 1985 and 1989	0.42	0.49	1.00	0.00
Dummy Variable for 1992, 1995 and 1998	0.42	0.49	1.00	0.00

Note:

Descriptive statistics are calculated across 20 manufacturing industries observed in 7 different years. Hourly output per worker refers to the 1991 New Taiwan dollar value. Capital expenditure per worker refers to new capital expenditures per worker in 1991 New Taiwan dollars.

Regarding the schooling variables, the mean of S across the 140 observations is 9.54. The standard deviation of the mean years of schooling is 1.36, and there is a fairly substantial range with a minimum value of 6.67 and a maximum of 13.14. As defined

earlier, R is referred to as the “rank of schooling by total labor force.” Its mean across the 140 observations is 40.73 (which is less than 50, the approximate value of the mean for the distribution of percentiles across all workers in the labor force in a given year). The minimum value of R is 24.25, while its maximum is 93.30. Note that these descriptive statistics are computed on the basis of percentiles that are derived from the distribution of schooling across all workers in the labor force in a given year.

The market-signal view does not clearly specify the relevant group over which relative educational attainment is to be gauged--that is, the relevant distribution to which the percentiles pertain. The obvious baseline distribution is the entire labor force, and we have just reported the descriptive results for R when it is based on that overall group. Additional possibilities are feasible, however, and we also consider these in our analyses in order to assess the robustness of our findings and conclusions.

Also shown in Table 2 is the “rank of schooling by 5-year age cohorts.” In this case, r refers to the percentile associated with an individual’s years of schooling based on the distribution derived from all workers in the labor force who are in the same 5-year age cohort. R is then just the mean of r defined in this way for each worker in the particular industry (and for the particular year). A basic argument for this approach is that employers do not compare educational attainment across age cohorts due to changes in educational standards and the general increase in educational opportunities across time in Taiwan.¹⁰ Across the 140 observations, the mean of “rank of schooling by 5-year age cohorts” is 38.10. This mean is similar to, albeit slightly smaller than, the mean of the “rank of schooling by total labor force.”

In the next stage, we define a relative educational attainment variable in which the distribution is separated by gender. In Table 2, this variable is “rank of schooling by gender.” For this variable, the percentiles pertain to the distribution of years of schooling completed by all workers in the labor force who are of the same gender (either male or female). We investigate this variable on account of the possibility that employers may compare the relative educational attainment of workers separately by gender (due perhaps to gender differences in curricula, experiences or performances). As shown in Table 2, the mean of “rank of schooling by gender” is 40.12, and its

¹⁰ Similarly, in calculating his *edr* scores, Sorensen (1979, p.371) used 3-year and 5-year age cohorts.

standard deviation is 10.92.

“Rank of schooling by gender and age” is based on the most specific definition of the pertinent distribution to use in gauging relative educational attainment. In this case, the percentile refers to a person’s ranking in the distribution of completed years of schooling among all workers in the labor market who are of the same gender and are in the same 5-year age cohort. This way of calculating r offers the greatest predictive power if employers rank workers’ educational attainment separately by age and gender.

Each of these different ways of calculating r --by the total labor force, by age cohorts, by gender and by gender and age--is also used in calculating a corresponding *edr* score based on Equation 3. These variables are shown in Table 2 as “*EDR* of schooling by total labor force,” “*EDR* of schooling by 5-year age cohort,” “*EDR* of schooling by gender” and “*EDR* of schooling by gender and age.” The descriptive statistics of these are also shown in Table 2.

In addition, Pearson correlation coefficients for several of these variables are shown in Appendix 2. Our dependent variable (i.e., the logged hourly output) has a positive correlation with the logged mean years of schooling as well as with the different types of logged mean schooling percentile ranking. They show that there are strong positive bivariate relationships among productivity and worker’s educational attainment and their relative educational ranking in the labor market. To estimate the net effects of years of schooling and schooling percentile ranking on productivity, multivariate analysis is required.

Regression Results

The first set of regression results are shown in Table 3. Model 1 in Table 3 includes the control variables--capital expenditures per worker, mean years of firm tenure and dummy variables to indicate time period--plus mean years of schooling.¹¹ Because the dependent variable as well as the continuous independent variables are all logged, the coefficients may be interpreted as elasticities.

¹¹ We do not report the estimated fixed effects for the 20 industries, but they are available from the author upon request.

Table 3: Weighted Least-Squares Estimates for Fixed-Effect Models of Labor Productivity in Taiwanese Manufacturing Industries, 1979-1998

Variable	Model 1	Model 2	Model 3
Log of Capital Expend. per Worker	-1.139 ** (0.440)	-1.285 ** (0.451)	-1.147 ** (0.440)
Log of Capital Expend. per Worker Squared	0.067 ** (0.023)	0.077 ** (0.024)	0.068 ** (0.023)
Log of Mean Years of Firm Tenure	0.005 (0.174)	0.104 (0.183)	0.035 (0.179)
Dummy Variable for 1982,1985 and 1989	0.207 ** (0.083)	0.330 ** (0.075)	0.214 ** (0.084)
Dummy Variable for 1992, 1995 and 1998	0.513 ** (0.134)	0.785 ** (0.105)	0.529 ** (0.136)
Log of Mean Years of Schooling	1.755 ** (0.492) [0.294]		1.561 ** (0.551) [0.262]
Log of Rank of Sch. by Total Labor Force		0.463 * (0.208) [0.136]	0.178 (0.226) [0.052]
R-square	.902	.896	.903
Adjusted R-square	.881	.873	.880

Note:

1. Dependent variable is log of hourly output per worker.
2. Standard errors are shown in parentheses; the standardized coefficients (i.e., beta) of education-related variables are shown in brackets.
3. The star * indicates $p < .05$; ** indicates $p < .01$; the significance level of our key variables is based on one-tailed tests.
4. All models are fixed-effect models. Due to space limitations, we do not report the parameter estimates and standard errors for the 19 industry dummy variables in each model. The complete information is available from the author upon request.

In Model 1, the coefficient for the mean years of schooling is substantively large as well as statistically significant at the .01 level. The coefficient of 1.76 indicates that a 1% increase in the mean years of schooling results in a net increase of 1.76% in labor productivity. This result is inconsistent with the credentialism view which contends that

schooling has no effect on economic productivity.

Model 2 includes the control variables plus R , the percentile rank of schooling, in this case by the total labor force. In Model 2 the coefficient for R is .46 and is statistically significant at the .05 level. This coefficient indicates that a 1% increase in R increases labor productivity by .46%. This net effect is substantial, but it is considerably less than the estimated net effect of the mean years of schooling in Model 1. Although the mean years of schooling and the percentile rank of schooling are not calibrated in terms of the same units, their coefficients in these models can, nonetheless, be directly compared because they refer to elasticities which are independent of the units of measurement. We also report the standardized coefficients (i.e., beta) of these different schooling measures to clarify their relative importance.

In Model 3 in Table 3, both S , the mean years of schooling, and R , the percentile rank of schooling, are included in the specifications (along with the control variables). The estimates of this regression clearly indicate that the mean years of schooling has a more important effect on labor productivity than does the percentile rank of schooling. In Model 3, the coefficient for R is substantially reduced and is not statistically significant at any conventional level. By contrast, the coefficient for the mean years of schooling retains both its substantive as well as statistical significance. As shown in Table 3, this coefficient is 1.56, indicative that a 1% increase in the mean years of schooling results in an increase of 1.56% in labor productivity net of the effects of the other variables in the model. This coefficient is statistically significant at the .01 level.

In Table 4, we report the results for other similar regression models that we estimate using percentiles which are based on other definitions of the relevant reference distribution. Model 4 in Table 4 includes R when it is based on 5-year age cohorts. In Model 5, R is computed separately by gender. In Model 6, both gender and the 5-year age cohorts are used to define the relevant reference distribution to which R pertains.

The empirical results for Model 4, Model 5 and Model 6 in Table 4 are all consistent with and, in fact, mirror the general conclusion that we mentioned above with regard to Model 3 in Table 3. That is, the mean years of schooling retains both its substantive as well as statistical significance regardless of which of these other ways is used to calculate R . In each of the three models, the mean years of schooling is statistically significant at

the .01 level, and the estimated coefficient is 1.61 or greater. By contrast, *R* is not statistically significant at any conventional level in Model 4, Model 5 or Model 6.

Table 4: Weighted Least-Squares Estimates for Fixed-Effect Models of Labor Productivity in Taiwanese Manufacturing Industries, 1979-1998

Variable	Model 4	Model 5	Model 6
Log of Mean Years of Schooling	1.649 ** (0.598) [0.277]	1.608 ** (0.543) [0.270]	1.775 ** (0.537) [0.298]
Log of Rank of Sch. by 5-year Age Cohort	0.105 (0.335) [0.035]		
Log of Rank of Schooling by Gender		0.139 (0.214) [0.041]	
Log of Rank of Schooling by Age and Gender			-0.021 (0.213) [-0.007]
R-square	.902	.902	.902
Adjusted R-square	.880	.880	.880

Note:

1. The dependent variable is the log of the hourly output per worker.
2. Standard errors are shown in parentheses; the standardized coefficients (i.e., beta) of education-related variables are shown in brackets.
3. The star * indicates $p < .05$; ** indicates $p < .01$; the significance level of our key variables is based on one-tailed tests.
4. All models also include (as do previous models shown in Table 3) controls for capital expenditures per worker, the mean number of years of firm tenure, two dummy variables for the time period and the 19 parameters of the industry dummy variables for fixed effects. These estimates are available from the author upon request.

In Table 5, we present the results for the estimation of the regression models in which Sorensen's (1979) *EDR* scores are used instead of *R*.

In Model 7, *EDR* is based on the total labor force, as a whole, and is included in the equation without the mean years of schooling (although the other control variables that are used in the previous models are also included as control variables in all of the models shown in Table 5). The estimated coefficient for *EDR* in Model 7 is fairly substantial

(i.e., .81) as well as statistically significant at the .01 level. Thus, *EDR* does have some explanatory power when it is the only education variable in the equation.

Table 5: Weighted Least-Squares Estimates for Fixed-Effect Models of Labor Productivity in Taiwanese Manufacturing Industries, 1979-1998

Variable	Model 7	Model 8	Model 9	Model 10	Model 11
Log of the Mean Years of Schooling		1.164 ** (0.576) [0.212]	1.371 ** (0.577) [0.230]	1.352 ** (0.570) [0.227]	1.585 ** (0.564) [0.266]
Log of EDR of Schooling by Total Labor Force	0.813 ** (0.232) [0.331]	0.520 * (0.271) [0.195]			
Log of EDR of Schooling by 5-year Age Cohort			0.320 (0.253) [0.153]		
Log of EDR of Schooling by Gender				0.384 (0.277) [0.153]	
Log of EDR of Schooling by Age and Gender					0.155 (0.251) [0.064]
R-square	0.902	0.905	0.903	0.904	0.902
Adjusted R-square	0.880	0.883	0.881	0.882	0.880

Note:

1. The dependent variable is the log of the hourly output per worker.
2. Standard errors are shown in parentheses; the standardized coefficients (i.e., beta) of education-related variables are shown in brackets.
3. The star * indicates $p < .05$; ** indicates $p < .01$; the significance level of our key variables is based on one-tailed tests.
4. All models also include (as do previous models shown in Table 3) controls for capital expenditures per worker, the mean number of years of firm tenure, two dummy variables for the time period and the 19 parameters of industry dummy variables for fixed effects. These estimates are available from the author upon request.

In Model 8, however, the mean number of years of schooling is then added as an additional independent variable. The results for Model 8, as shown in Table 5, indicate that the net effect of *EDR* (based on the total labor force) is reduced to .520, but it is statistically significant at least at the .05 level in a one-tailed test. Also, it should be noted that in Model 8, the net effect of the mean number of years of schooling (i.e., 1.16)

is still statistically significant. Thus, the results for Model 8 indicate that both the mean number of years of schooling and *EDR* (based on the total labor force) have net effects on labor productivity and that the former is larger than the latter.¹²

Table 5 also shows the results for Models 9 through 11. In Model 9, *EDR* is constructed on the basis of the 5-year age cohorts. In Model 10, *EDR* is constructed separately by gender. In Model 11, *EDR* is based on both the 5-year age cohorts as well as on gender. As shown in Table 5, these *EDR* variables are not statistically significant at the .05 level in one-tailed tests in any of these models. In sum, the only result where an *EDR* variable has a net effect that is statistically significant at the .05 level (in a one-tailed test) is in Model 8 where *EDR* is based on the total labor force, as a whole. Indeed, in all of our analyses, this is the only result where a variable derived from the ordinal rank of educational attainment is found to be statistically significant net of the mean number of years of schooling.

Additionally, our data cover 20 years and consist of 20 manufacturing industries as mentioned earlier. It is also important to determine if the net effect of schooling on productivity has changed over time or has differed in specific industrial groups. We therefore replicate the models shown in Tables 3 to 5 by dividing our data into two parts by time (T1 refers to 1979, 1982, 1985 and 1989; T2 refers to 1992, 1995 and 1998). Similarly, two groups (G1 refers to industries 1, 2, 8, 9, 10, 13, 14, 17, 18 and 19 which have higher labor hourly output; G2 refers to the other 10 industries with lower labor hourly output) are also analyzed separately. The results are reported in Appendix 3 and Appendix 4, respectively.

In general, the net effects of the mean number of years of schooling on productivity are greater than our other measures of schooling, and these findings are consistent with the results reported above. Specifically, however, we find that the effects of the mean number of years of schooling on productivity in T1 are greater than those in T2 in most models. This finding is largely consistent with the findings reported in the literature

¹² In assessing the relative sizes of the education effects, we compare elasticities as is common in productivity research. However, in terms of standardized coefficients (i.e., beta), the net effect of the mean number of years of schooling in Model 8 is approximately the same as is that for *EDR*. We prefer to compare elasticities, however, because that practice is more conventional in productivity and because the comparison of standardized coefficients in this case is very much affected by the fact that the standard deviation of *EDR* is much more than twice as large as the standard deviation for the mean years of schooling.

pertaining to the economics of education (e.g., Layard and Psacharopoulos 1974) which contend that the effects of schooling should decline over time if it is a pure screening device. For the two industrial groups, the effect of schooling on productivity is greater for industries with higher labor hourly output than for industries with lower labor hourly output. This finding suggests the importance of an interaction between the effects of education and industrial characteristics. We hope that future research will consider this more complex topic further.

VII. Discussion and Conclusions

Our primary research concern has been to empirically evaluate the relationship between educational attainment and labor productivity since the nature of this relationship has important implications for understanding how economic inequality is generated in the labor market. Previous literature on this topic may be organized into three major theories of the role of education in the labor market: (1) the technical-functional view; (2) the market-signal view; and (3) the credentialism view. Each of these theories has different implications as to how indicators of educational attainment affect labor productivity. As we have mentioned, these perspectives are not necessarily mutually exclusive in real labor markets. The employment system, for example, may provide advantages to those with more education both because their education has raised their productive capacities (human capital) and they have latent traits, such as the capacity to learn new things easily, that are signaled by more years of educational attainment (screening). In this paper, we try to clarify how these three theories, in their purest forms, can be empirically distinguished.

It might be argued that our findings are suspect due to the collinearity between the mean number of years of schooling and the percentile rank of schooling. While we agree that, in general, multicollinearity can sometimes obscure the implications of a given set of research results, we do not believe that multicollinearity is a problem in our analysis. Multicollinearity refers to the situation when two (or more) variables in a regression are jointly significant (in terms of the F-test), but none of them are individually significant (in terms of their respective t-tests); in this situation, the researcher knows that at least one of the variables can not be dropped from the regression

(because the F-test is significant), but the t-tests do not clearly indicate which variable is significant (Goldberger 1991, p. 245). While this situation of multicollinearity certainly obscures the implications of a set of results, it simply does not apply to our findings because they clearly demonstrate which variable is statistically significant, and that is the mean number of years of schooling. Furthermore, the same result is consistently shown in other models.

In general, the strongest and most consistent finding from our analyses is the large net effect of the mean number of years of schooling on labor productivity in manufacturing industries. The mean number of years of schooling is, in fact, statistically significant in all of these models. Its estimated coefficient is always larger than is the estimated coefficient for any other educational variable that is included in the models. What is worth noting too is that labor productivity in a manufacturing firm seems to be highly elastic with respect to the mean number of years of schooling attained by its workers, and this result is evidently net of the control variables and of any measure of relative educational attainment.

We interpret this result as providing strong *prima facie* evidence for the technical-functional view. Contrary to the credentialist claim that education has no economic value, labor productivity in manufacturing industries is clearly and directly increased when workers have more years of schooling. Furthermore, this increase is still obvious and substantial even after controlling for any indicator of the extent of relative educational attainment completed by workers. That is, increased schooling *per se* increases labor productivity independently of the extent to which the educational levels of some workers may be ranked more highly than those of other workers. Thus, this finding is inconsistent with the market-signal view which emphasizes the importance of relative educational attainment due to the assumption that schooling does not directly augment human capital but rather only certifies those who possess greater abilities.¹³

In other words, of the three major theories that we have discussed, our results most strongly support the technical-functional view since the mean number of years of schooling is consistently the most important education variable in the regression analyses,

¹³ Interestingly, Ross and Mirowsky (1999) find that the years of schooling is also the dimension of education that has the largest effect on self-reported general health and physical functioning.

and this is consistent with and predicted by the technical-functional view. For this reason, we can also clearly rule out the credentialist view which predicts that economic productivity is unrelated to education. Further, even though Jiang's (1990) methodology differs greatly from ours, he also concludes that there is little empirical support for the credentialist view when applied to the contemporary Taiwanese labor market (also see Yu and Chu 1998; Liu and Li 2001).

As concerns the market-signal view, our findings are not strongly supportive, but it could be argued that some limited support for this theory is evident in our regression results. Among all of the models that we estimate which include both the mean number of years of schooling and some indicators related to educational attainment (i.e., some measures of *R* or *EDR*), the latter variables are statistically significant at the .05 level in one case, more precisely Model 8, which includes *EDR* as computed on the basis of the total labor force. Although the coefficient for the mean number of years of schooling is clearly larger and more important than is the coefficient for *EDR* in Model 8, the fact that the latter coefficient is fairly large as well as statistically significant at the .05 level (at least in a one-tailed test) provides some support for the market-signal view.

In addition, while limited support of the market-signal view may be evident in Model 8, we argue that what is needed is a more sophisticated version of that approach. Strong and simplistic versions of the market-signal view--according to which only relative educational attainment matters and schooling does not directly augment labor productivity--most probably need to be reconsidered. Further theoretical developments may require a model which incorporates aspects of both the technical-functional view as well as the market-signal view. This contention may be consistent with the view of Bidwell and Friedkin (1988, p. 454) who state that "What is learned and what is certified as having been learned on average are strongly related, making it very difficult to determine the degree to which labor markets are responsive to workers' capabilities or credentials. It may be more judicious to regard learning and gaining credentials as tightly linked mechanisms through which schooling affects employability." The need for this sort of model has also been argued for by Weiss (1995, p. 134) who states that "Sorting models [i.e., the market-signal view] of education can best be viewed as extensions of human capital models." We believe that future theoretical work on this

topic should more fully incorporate the interrelations among educational attainment, employer and firm practices regarding hiring and remuneration and market conditions related to the degree and nature of competitive pressure.

We emphasize, however, that none of our results directly support the human capital theory of *wages per se*. Although our findings are consistent with one assumption of that theory--namely, that education augments labor productivity--our analyses do not address other crucial assumptions of the human capital theory. In particular, we have not presented any evidence that *wages* among individuals derive solely from their productivity; indeed, we have not presented any evidence at all regarding wages. It is also certainly beyond the scope of this paper to consider whether wages are set on the basis of competitive market forces (Lang and Dickens 1988; Sakamoto and Chen 1991). In other words, our findings are not broad enough to provide direct support for critical assumptions of the human capital theory of *wages* although our results are probably consistent with at least one of the assumptions of that theory. From a strictly neoclassic economic point of view, it might be argued that the net effect of *EDR* as evidenced in Model 8 derives from some nonlinearity in the effect of years of schooling on productivity. Because the mean number of years of schooling weighs each year of schooling equally, the remaining net effect of *EDR* in Model 8 may reflect the greater productivity associated with the higher years of schooling (i.e., college years) because *EDR* is more sensitive to the upper end of the schooling distribution.

We should furthermore point out that although our results indicate that the number of years of schooling has a strong net effect on productivity, they do not demonstrate that this effect is an entirely direct result of improvements in cognitive skills. While we would suspect that cognitive skills are at least partly involved in this increased productivity, it is also quite plausible that attending school longer increases a person's work discipline as well as improves his or her social skills which are also important sources of labor productivity. In addition, schools may sometimes directly impart work skills that are directly relevant to production processes. In any event, in none of our analyses do we use any direct measures of cognitive skills *per se*.

Finally, one important, albeit obvious, limitation in our analysis is that the data pertain only to Taiwanese manufacturing industries in recent decades. We therefore do

not present any evidence which would permit us to argue that our conclusions apply to other sectors of the Taiwanese economy or to other post-industrial economies, such as the United States. However, it is worth pointing out that a major conclusion of Tam and Tang's (1998, p. 21) review of the American literature is that the "substantial returns from additional years of schooling mostly reflect a gain in labor market productivity....the returns to the quantity of schooling are driven by the productive significance of learning in school. The presence of ability sorting does not lead to substantial bias in the returns to schooling. The signaling value of schooling is at best a very minor source of the substantial returns to additional years of schooling." We hope that future research will expand upon our efforts here.

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Appendix 1: List of Manufacturing Industry Categories

IND 1	Food
IND 2	Beverage and Tobacco
IND 3	Textile
IND 4	Clothing?Wearing? Apparel and Accessories
IND 5	Leather and Fur Products
IND 6	Wood and Bamboo Products and Non-metallic Furniture
IND 7	Paper Products and Printing
IND 8	Chemical Materials
IND 9	Chemical Products
IND 10	Petroleum and Coal Products
IND 11	Rubber Products
IND 12	Plastic Products
IND 13	Non-metallic Mineral Products
IND 14	Basic Metal
IND 15	Fabricated Metal Products
IND 16	Machinery and Equipment
IND 17	Electrical and Electronic Machinery Equipment
IND 18	Transport Equipment
IND 19	Precision Instruments
IND 20	Miscellaneous Industrial Products

Appendix 2: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LNOUT	1.000									
LNMSCH	0.713	1.000								
LNSPT	0.641	0.783	1.000							
LNSPA	0.655	0.795	0.924	1.000						
LNSPG	0.617	0.768	0.986	0.893	1.000					
LNSPAG	0.643	0.763	0.972	0.943	0.969	1.000				
LNEDRT	0.538	0.732	0.905	0.952	0.884	0.901	1.000			
LNEDRA	0.540	0.736	0.865	0.953	0.832	0.891	0.972	1.000		
LNEDRG	0.525	0.733	0.899	0.931	0.901	0.903	0.982	0.947	1.000	
LNEDRAG	0.531	0.740	0.871	0.942	0.863	0.911	0.911	0.980	0.974	1.000

Note: All bivariate correlations are significant at the .01 level.

Appendix 3: Net Effects of Schooling Measures on Productivity by Time

	LNMSCH		LNEDRT		LNEDRA		LNEDRG		LNEDRAG	
	b	beta	b	beta	b	beta	b	beta	B	beta
	(s.e.)		(s.e.)		(s.e.)		(s.e.)		(s.e.)	
Model 1	T1	2.101*	0.354							
		(0.399)								
	T2	3.846*	0.553							
		(0.694)								
Model 7	T1		0.640*	0.285						
			(0.170)							
	T2		1.437*	0.633						
			(0.201)							
Model 8	T1	2.503*	0.421	-0.191	-0.085					
		(0.730)		(0.290)						
	T2	1.389*	0.612	0.173	0.025					
		(0.388)		(0.388)						
Model 9	T1	2.834*	0.477			-0.377	-0.173			
		(0.667)				(0.275)				
	T2	1.004*	0.471			1.231	0.177			
		(0.365)				(1.155)				
Model 10	T1	2.065*	0.348					-0.017	0.007	
		(0.708)						(0.272)		
	T2	1.371*	0.591					-0.002	0.001	
		(0.363)						(1.193)		
Model 11	T1	2.281*	0.384						-0.090	-0.040
		(0.637)							(0.247)	
	T2	1.109*	0.456						1.046	0.151
		(0.357)							(1.178)	

Note:

1. T1 refers to data from 1979, 1982, 1985 and 1989; T2 refers to data from 1992, 1995 and 1998.
 2. The star * indicates $p < .05$ (one-tailed test).
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Appendix 4: Net Effects of Schooling Measures on Productivity by Industries

	LNMSCH		LNEDRT		LNEDRA		LNEDRG		LNEDRAG	
	B	beta	b	beta	b	Beta	b	beta	B	beta
	(s.e.)		(s.e.)		(s.e.)		(s.e.)		(s.e.)	
Model 1	G1	2.383*	0.346							
		(0.420)								
	G2	2.896*	0.794							
		(0.396)								
Model 7	G1		0.589*	0.182						
			(0.216)							
	G2		0.841*	0.493						
			(0.216)							
Model 8	G1	3.222*	0.468	0.494*	0.153					
		(0.630)		(0.280)						
	G2	2.680*	0.102	0.174	0.102					
		(0.478)		(0.214)						
Model 9	G1	3.514*	0.511			0.730*	0.212			
		(0.667)				(0.265)				
	G2	2.838*	0.778			0.052	0.033			
		(0.454)				(0.198)				
Model 10	G1	3.307*	0.481					0.514*	0.165	
		(0.658)						(0.285)		
	G2	2.315*	0.635					0.406*	0.226	
		(0.501)						(0.221)		
Model 11	G1	3.641*	0.529						0.751*	0.229
		(0.598)							(0.266)	
	G2	2.556*	0.154						0.270	0.154
		(0.206)							(0.206)	

Note:

1. G1 refers to industries 1, 2, 8, 9, 10, 13, 14, 17, 18 and 19; G2 refers to the other 10 industries.
 2. The star * indicates $p < .05$ (one-tailed test).
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學校教育在台灣勞動市場中扮演的角色： 人力資本，篩選機制，或文憑主義？

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中 文 摘 要

個人的教育與其社會經濟成就之間有密切的關係。然而，這種關係係源自於其人力資本的增加與生產能力的提升？勞動市場之篩選？或僅是文憑主義的作用？則為有關社會階層化研究的普遍爭議。雖然，這三種說法對教育與社會經濟地位的關聯性所提出之理由各有不同，但卻未見學界有系統的比較各理論之適用性，也不曾對此等理論進行過決斷性的驗證。我們經由分析各種代表學校教育的量化指標對經濟生產力產生的影響效果，試圖釐清學校教育在勞動市場中所扮演的角色。實際操作上，本文使用了近二十年來的台灣人力運用調查資料及各相關的官方統計報告，以產業別為單位，分析了製造業勞工之教育成就與其平均生產力的關係。部分結果呈現出台灣勞動市場篩選的事實，但對人力資本理論的支持程度則更為明顯。

關鍵字：人力資本、篩選標準、文憑主義、勞動生產力

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