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IZA DP No. 11125

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ABSTRACT

Human Capital, Signaling, and Employer Learning: What Insights Do We Gain from Regression Discontinuity Designs?*

Several recent papers employ the regression discontinuity design (RDD) to estimate the causal effect of a diploma (or similar credentials) on wages. Using a simple model of asymmetric information, I show that RDD estimates the information value of a diploma. A positive information value arises if employers, unable to observe the test score that determines diploma receipt, infer that workers with a diploma have higher average productivity than those without. Crucially, a diploma can have information value regardless of whether workers' productivity is solely determined by acquisition of knowledge and skills through studying (the pure human capital model) or whether studying has no effect on productivity (the pure signaling model). Thus, while RDD estimates of diploma effects are evidence for information frictions and statistical discrimination, they do not help to distinguish between human capital and signaling. However, with longitudinal data, RDD can be used to estimate the speed of employer learning, since RDD coefficients are direct estimates of (differences in) expectation errors.

JEL Classification: C2, D8, J2

Keywords: human capital, signaling, employer learning, statistical discrimination, regression discontinuity design

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1 Introduction

Why do some people get more education than others, and why are wages and education positively correlated? According to the human capital view, education raises productivity and hence wages, and individuals who are more efficient at learning respond to this incentive more strongly (Becker, 1964; Ben-Porath, 1967). In contrast, the pure signaling view denies any productive effect of education. Instead, it assumes that individuals' study efficiency is positively correlated with productivity, and argues that more-skilled individuals choose higher levels of education to signal their higher productivity to employers (Spence, 1973). The two theories are difficult to distinguish in the data, as they both predict positive relationships between wages and education, as well as between education and skill measures such as IQ.[1]

Evidence in favor of the pure signaling view is especially hard to come by. For example, a comparison of two workers with the same number of years in school, where one obtained a graduation diploma but the other did not, may be contaminated by heterogeneity in human capital accumulation that is unobserved to the econometrician but observed to employers. To address this problem, researchers have searched for exogenous variation in diplomas (or similar credentials) to estimate their signaling value. Regression discontinuity designs (RDDs) using the exam score that determines diploma receipt have become especially popular in recent years. By focussing on individuals close to the threshold that must be cleared to obtain the diploma, one can consistently estimate the causal effect of the diploma on wages. It is often argued that a positive estimate constitutes evidence in favor of the signaling view of education.[2]

In this paper I show instead that random assignment of signals via an RDD cannot be used to distinguish between signaling and human capital theories. Wage differences detected by an RDD do reflect differences in beliefs that employers attach to different diploma statuses. However, these differences must be due to comparisons of large groups of workers on either side of the score threshold, since employers do not know which individuals are close to the threshold. In the sample that the employers' comparisons are based on, there are true productivity

[1]Throughout the paper, I use productivity in the same way as Spence (1973, p.361): "For productivity the reader may read 'what the individual is worth to the employer.' There is no need to rely on marginal productivity here."

[2]For instance, Clark and Martorell (2014) propose using an RDD to estimate the signaling value of a high school diploma in the US. They write (p.282):

> [A diploma] cannot affect productivity because it is essentially only a piece of paper, despite the strong correlation between productivity and diploma receipt, precisely the reason why it could act as a productivity signal. This implies that we could, conceivably, estimate the signaling value of a diploma by randomly assigning it among a small group of workers. By virtue of the random assignment, the signaling value of the diploma would be captured by the earnings advantage enjoyed by the workers randomly assigned to receive it.

By estimating the signaling value of a high school diploma using an RDD, they aim to "distinguish between the human capital and signaling theories" of education (p.283).

Acemoglu and Autor (2009, p.45) argue that "the implications of unobserved heterogeneity and signaling are often similar" and suggest that the best approach to determine whether signaling is important is to use exogenous variation in credentials as in Tyler, Murnane, and Willett (2000). See also footnote 4 below.

differences by diploma status. Crucially, these productivity differences could be due to variation in accumulated human capital, or due to a correlation between productivity and study efficiency when knowledge has no effect on productivity (the pure signaling view), or due to a combination of both. Unfortunately, there is no way to tell from the RDD evidence what the source of the productivity differences is.

I develop a simple model that clarifies these points. The model is one of asymmetric information, where employers must infer workers' productivity based on some signal such as a diploma. Workers can influence the probability of receiving the diploma by acquiring knowledge and skills through studying, and they differ by study efficiency. Despite the premise that employers must solve a signal extraction problem, there is still room in my model for both the pure human capital and the pure signaling views of education in the following sense. Worker productivity may either be completely determined by studying, it may be unaffected by studying, or it may both be a function of studying and pre-determined characteristics. Thus, I take as the central question in the human capital versus signaling debate whether education has a causal effect on productivity, and *not* whether there exist information frictions in the labor market. Indeed, human capital theory suggests that, regardless of the existence of information frictions, policy should remove barriers that prevent people from acquiring their desired level of education. In contrast, pure signaling theory suggests that education may be socially harmful, leading to very different policy implications.

Although the conclusion of this paper is negative with respect to the ability of RDD to address the human capital versus signaling question, I do offer two insights which I hope readers will find useful. First, I show that RDD estimates the *information value* of a diploma or similar certification, the causal effect of the diploma on employer's beliefs about worker productivity. This parameter is of interest for our understanding of the labor market and also for policy. If the information value is estimated to be positive, then this is evidence for information frictions, for the ability of a diploma to alleviate these frictions, and for statistical discrimination by employers. If the information value appears to be zero, then this suggests that either information frictions are absent, or, perhaps more likely, that the diploma does not carry any useful information—and the latter would be cause for concern to policy makers.

The concept of the information value that I use in this paper is arguably related to the 'signaling value' referred to in previous literature. My contribution is to define this concept in relation to a theoretical model. In this way, misunderstandings can be avoided. For instance, it becomes clear that RDD or any other quasi-experimental design cannot estimate the information value "net of human capital effects" (Tyler, Murnane, and Willett, 2000). Any positive information value will reflect differences in accumulated human capital if the knowledge required to pass the test is useful in production.

Second, I derive implications of diploma RDD coefficients for employer learning. Given that diploma RDDs estimate employers' initial beliefs, the connection with the employer learning literature is natural.[3] To build intuition, I first discuss a simple extension to the theoretical model. I show that, if worker ability gets revealed over time, then an RDD using wages long after graduation as the outcome will estimate a zero diploma effect (again, regardless of the relative importance of human capital and signaling). I then present a more general framework in which worker productivity is time-varying. I show that if wages are observed at several points in time, then diploma RDDs can be used to trace out the time path of (differences in) expectation errors, thus measuring the speed at which employers learn about worker ability. This result does not depend on the functional form and distributional assumptions made in previous work.

The focus of this paper is RDD because it is arguably the most common research design for estimating causal effects of diplomas or other certifications (see the next paragraph). However, the conclusions generalize to any setting in which diplomas are (quasi-)randomly assigned. Regardless of the identification strategy employed, positive estimates of a diploma's information value (or signaling value) cannot be evidence in favor of pure signaling. This is because diplomas will also have information value in a human capital model featuring asymmetric information.[4]

There are already several papers estimating diploma RDDs and their number is sure to increase in the coming years. Clark and Martorell (2014) estimate a zero effect of high-school diploma receipt in data from Texas. Di Pietro (2017) and Feng and Graetz (2017) use RDDs to estimate the causal effects of degree class (a coarse measure of university performance) on early labor market outcomes in the UK. Both papers find no effect on employment, but Feng and Graetz (2017) estimate a positive effect on the probability of working in a high-wage industry, as well as on (expected) industry wages and earnings. In Feng and Graetz (2017) we are careful to point out that our estimates do not speak to the signaling versus human capital question.[5] Freier, Schumann, and Siedler (2015) estimate positive earnings effects of graduating with honors for German law graduates. While their setting lends itself to a typical 'diploma RDD,' they do not actually implement this due to lack of statistical power. However, their differences-in-differences design closely mimics an RDD. With reference to Feng and Graetz (2017), they acknowledge that their evidence cannot distinguish between signaling and human capital. Khoo and Ost (2017) use an RDD to estimate the effects of Latin honors in the US. They find positive effects on wages in the first two years after graduating, but not in the third, consistent with employer learning.

[3] See for instance Altonji and Pierret (2001), Arcidiacono, Bayer, and Hizmo (2010), Farber and Gibbons (1996), Fredriksson, Hensvik, and Nordström Skans (2015), Gibbons, Katz, Lemieux, and Parent (2005), and Lange (2007).

[4] Tyler, Murnane, and Willett (2000) estimate the information value (they call it signaling value) of the General Educational Development (GED) credential in the US. Since there are differences in passing standards across states, Tyler, Murnane, and Willett (2000) are able to essentially compare earnings between individuals with the same raw score but different GED status. They are motivated by the observations that "[it] has proved difficult (...) to distinguish between human capital and signaling explanations of the observed relationship between education and earnings" (p.431) and that "[ideal] data for identifying the returns to a signal would contain exogenous variation in signaling status among individuals with similar levels of human capital" (p.432). In this paper I affirm the latter statement, but emphasize that estimating the return to a signal is not sufficient for distinguishing between human capital and signaling theories.

[5] We made the contrary claim in the first working paper version of that article, before realizing our error.

Their interpretation (p.4) is in line with the argument in this paper: "[It] is possible that firms view Latin honors as a signal of ability, but this ability was learned in college as opposed to being an innate trait as in Spence's original model. As such, the signaling value of Latin honors could theoretically operate through a human capital effect."[6,7]

The plan of the paper is as follows. Section 2 presents the model. Section 3 characterizes a separating equilibrium and proves its existence. Section 4 clarifies what RDD estimates in relation to the model. Section 5 first extends the model to incorporate learning, and then presents a more general framework to demonstrate how RDD can be used to estimate the speed of learning. Section 6 offers a brief concluding discussion of alternative approaches to testing signaling theory.

2 A model of diplomas and labor market entry

I begin with an informal overview. The model economy is populated by large numbers of risk-neutral workers as well as risk-neutral entrepreneurs who run firms employing the workers. All workers first study at school. At the end of their studies they take a test, and if they score above a known threshold, they receive a diploma. Workers can influence their test score through knowledge acquisition, but cannot manipulate the score precisely. Workers differ by innate and time-invariant talent, which determines the cost of acquiring knowledge. Productivity is an increasing function of acquired knowledge, or of innate talent, or of both. After graduation, workers enter a perfectly competitive labor market and are paid their expected marginal product. Prior to employing them, firms know nothing about workers apart from whether they have received a diploma. Hence, there are at most two distinct values that starting wages may take. There is only one period of production activity, and no learning takes place. I also discuss two extensions of the model, one that allows for a second signal and hence wage variation conditional on diploma status, and one that includes learning.

I now turn to the formal exposition of the model, starting with test score production and diploma receipt. Worker i's test score z_i is the sum of her knowledge $k_i \geq 0$ and a noise term u_i,

[6] A further concern with the interpretation of diploma RDDs is the possibility that employers observe the underlying running variable. In that case, a positive diploma effect indicates limits on employers' ability to process information.

[7] There is a close connection between the literature on 'sheepskin effects' and the more recent stream of papers employing RDD to estimate degree effects. Both literatures claim to offer tests of signaling theory. Layard and Psacharopoulos (1974) argue that if signaling is important, then graduation should be a stronger indication of productive skills than mere attendance. Hence, there should be larger returns to an extra year of education when completion of that year coincides with a degree award. They do not find evidence of this in US data. However, subsequent literature has consistently documented substantial sheepskin effects (see for instance Jaeger and Page, 1996). It is questionable whether these findings are in support of signaling, since graduation years may feature a faster rate of human capital accumulation, and this may be known by employers if not measured by the econometrician. An alternative interpretation is that individuals face uncertainty about their returns to schooling, but partially resolve this uncertainty while in school. This causes low-return individuals to drop out, see Lange and Topel (2006).

which is revealed only after knowledge has been acquired,

$$z_i = k_i + u_i. \tag{1}$$

The noise is independently and identically distributed with mean zero. Let F_u denote its CDF, with unbounded support and the symmetry property $F_u(x) = 1 - F_u(-x)$.[8] The assumption that workers cannot perfectly set their test score is realistic, but it is also needed for the validity of an RDD that uses data generated from this model.

Workers incur a cost when studying, in wage units, of $\theta_i^{-1} c(k_i)$. Innate talent θ_i is strictly positive and continuously distributed with bounded support. The cost function is defined on $[0, \bar{k})$, with $\bar{k} < \infty$, and has the following properties:

$$c'(k) > 0 \text{ if } k > 0,\ c'(0) = 0; \qquad c''(k) > 0; \qquad \lim_{k \to \bar{k}} c(k) = \infty. \tag{2}$$

These properties will ensure existence of a separating equilibrium in which optimal knowledge is distributed over finite support.[9] Diploma status is indicated by d_i. Receipt of the diploma requires a non-negative test score,

$$d_i = \begin{cases} 0 & \text{if } z_i < 0 \\ 1 & \text{if } z_i \geq 0. \end{cases} \tag{3}$$

To complete the setup of the model, I specify the production side. Worker i produces p_i units of output. Productivity is a function of knowledge and innate talent as follows:

$$p_i = a_k k_i + a_\theta \theta_i, \qquad a_k, a_\theta \geq 0. \tag{4}$$

Equation (4) nests the pure human capital model where only knowledge affects productivity: $a_k > 0, a_\theta = 0$; the pure signaling model where only innate talent affects productivity: $a_k = 0, a_\theta > 0$ (recall that the cost of acquiring knowledge is an inverse function of innate talent); as well as a combination of human capital and signaling $a_k > 0, a_\theta > 0$.

3 A separating equilibrium in which diplomas have information value

Given the setup of my model, a suitable equilibrium concept is Bayesian Nash Equilibrium (BNE). In a BNE, workers set their knowledge level, and by implication the probability of obtaining the diploma, to maximize expected wages net of study costs, given the wage schedule offered by employers. In turn, employers' beliefs about workers' acquired knowledge and type,

[8] All functions in this paper are assumed to be differentiable as often as needed.

[9] Note that $\bar{k}$ could be a very large number, so the assumption of finite support is not a very restrictive one.

conditional on diploma status, are consistent with workers' actions. While there is a multiplicity of BNEs in this model, I am most interested in a separating equilibrium in which workers with a diploma are correctly expected to have acquired more knowledge than those without.[10] The following result claims existence of such an equilibrium.

Proposition 1. *Suppose that $a_k, a_\theta \geq 0$ and $a_k + a_\theta > 0$. There exists a Bayesian Nash Equilibrium in which workers' chosen knowledge level is a strictly increasing function of innate talent; and in which workers with diploma receive a wage w_1 that is strictly higher than the wage earned by workers without a diploma, w_0.*

To prove the claim, I start by characterizing the properties that such an equilibrium would have if it existed.

Suppose that $w_1 > w_0$ and consider the workers' optimal knowledge acquisition choice. The probability of receiving a diploma, given knowledge, is $1 - F_u(-k_i)$ which equals $F_u(k_i)$ due to the symmetrical distribution of the noise term. Hence, optimal knowledge is determined by solving the following optimization problem:

$$\max_{k_i \in [0,\infty)} F_u(k_i) w_1 + (1 - F_u(k_i)) w_0 - \theta_i^{-1} c(k_i). \tag{5}$$

The first-order necessary condition for an interior solution to (5) is

$$f_u(k_i)\,[w_1 - w_0] = \theta_i^{-1} c'(k_i), \tag{6}$$

and the second-order sufficient condition ensuring a local maximum is

$$f_u'(k_i)\,[w_1 - w_0] - \theta_i^{-1} c''(k_i) < 0.$$

Recall that k_i is non-negative and u_i has a symmetric distribution with mean zero. Therefore, $f_u'(k_i) \leq 0$. This together with the properties of the cost function (2), ensures that the second-order condition is always satisfied. The first- and second-order conditions can then be used to demonstrate that optimal knowledge at the interior solution is strictly increasing in talent θ_i and strictly increasing in the wage gap $w_1 - w_0$. To ensure that the interior solution delivers the global maximum, we need to rule out that $k_i = 0$ is optimal for some workers, which is done by assuming that the derivative of the cost function is zero at zero knowledge, as stated in (2).

I now turn to employers' beliefs. If the distribution of knowledge is non-degenerate, then the expected knowledge level of a worker with diploma is higher than that of one without. Let the CDF of optimal knowledge conditional on diploma status be denoted by $F_{k^*|d}$. Then we

[10] There is also a trivial pooling equilibrium in which employers pay the same wage to everybody, regardless of diploma status, and workers rationally refrain from studying. The test score and diploma status are then completely uninformative about worker types, reinforcing the employers' equal-pay strategy.

have $F_{k^*|d=1}(x) \leq F_{k^*|d=0}(x)$, with strict inequality for some x. In other words, $F_{k^*|d=1}$ first-order stochastically dominates $F_{k^*|d=0}$, implying that the expected value of k^* is higher for workers with a diploma.[11] The same argument applies to expected innate talent: it is also higher for workers holding a diploma, $F_{\theta|d=1}(x) \leq F_{\theta|d=0}(x)$. In a competitive market, wages equal the expected value of productivity conditional on diploma status, $w_i = \mathbb{E}[p_i|d_i]$. Since workers who possess a diploma have more knowledge on average than those who do not, they earn higher wages. This may be because higher expected knowledge implies higher levels of human capital, $a_k > 0$. Or it could be because higher expected knowledge implies higher levels of innate talent, implying higher productivity if $a_\theta > 0$. In sum, a diploma leads to higher wages whenever knowledge, or innate talent, or both, affect productivity.

Let the difference in wages between workers with diploma and those without be denoted by $\delta \equiv w_1 - w_0$. Then we can write, using (4),

$$\begin{aligned} \delta &= \mathbb{E}[p_i|d_i = 1] - \mathbb{E}[p_i|d_i = 0] \\ &= a_k \int_{S_{k^*}} xd\left(F_{k^*|d=1}(x) - F_{k^*|d=0}(x)\right) + a_\theta \int_{S_\theta} xd\left(F_{\theta|d=1}(x) - F_{\theta|d=0}(x)\right). \end{aligned}$$

Applying integration by parts, and using the fact that knowledge and talent have bounded support, we obtain

$$\delta = a_k \int_{S_{k^*}} \left(F_{k^*|d=0}(x) - F_{k^*|d=1}(x)\right) dx + a_\theta \int_{S_\theta} \left(F_{\theta|d=0}(x) - F_{\theta|d=1}(x)\right) dx. \tag{7}$$

The right-hand side of (7) is strictly positive (because $F_{\cdot|d=1}(x) \leq F_{\cdot|d=0}(x)$, with strict inequality for some x), and it is a function of δ since, by the FOC (6), δ affects knowledge choice and hence the distribution of the test score.

Thus, all that is needed for a separating equilibrium to exist is for the right-hand side of (7) to be bounded even as δ grows arbitrarily large. Since all terms on the right-hand side of (7) are either constants or CDFs that are integrated over finite support, this condition is satisfied. This completes the proof of Proposition 1.

[11] To see that $F_{k^*|d=1}(x) \leq F_{k^*|d=0}(x)$, note that

$$F_{k^*|d=1}(x) \equiv \Pr(k^* \leq x|z \geq 0) = \frac{\Pr(z \geq 0|k^* \leq x)\Pr(k^* \leq x)}{\Pr(z \geq 0)}$$

and

$$F_{k^*|d=0}(x) \equiv \Pr(k^* \leq x|z < 0) = \frac{\Pr(z < 0|k^* \leq x)\Pr(k^* \leq x)}{\Pr(z < 0)} = \frac{[1 - \Pr(z \geq 0|k^* \leq x)]\Pr(k^* \leq x)}{1 - \Pr(z \geq 0)}.$$

Comparing the two rightmost expressions, we see that $F_{k^*|d=1}(x) \leq F_{k^*|d=0}(x)$ requires $\Pr(z \geq 0|k^* \leq x) \leq \Pr(z \geq 0)$, which holds since $\Pr(z \geq 0) \equiv \Pr(z \geq 0|k^* < \infty)$.

4 RDD estimates the information value of a diploma, but cannot distinguish between signalling and human capital theories of education

Recall that the difference in wages between workers with diploma and those without is denoted by $\delta \equiv w_1 - w_0$. I call this the *information value* of the diploma, because in a separating equilibrium it reflects the difference in employers' beliefs about the productivities of workers with different diploma status. Here I show that an RDD that uses data generated by my model consistently estimates this value.

Before proceeding, it is worth noting that the model as stated does not *require* an RDD for estimation of δ. In fact, a comparison of mean wages by diploma status will suffice. In reality, however, this is unlikely to be the case, and a simple modification of the model demonstrates why. Suppose that employers receive a second signal about workers' ability, $s_i = \theta_i + \eta_i$, where η_i is an independently and identically distributed noise term. Suppose further that this signal, although it is correlated with type, cannot be controlled by the workers, and that workers acquire knowledge unaware of the value of the second signal. This signal will generate wage dispersion even conditional on diploma status. Moreover, because test scores vary with knowledge, which in turn is a deterministic function of innate talent, there will be a positive correlation between wages and test scores even conditional on diploma status. A comparison of mean wages by diploma status will then give an upwardly biased estimate of δ. However, an RDD would address this problem. To simplify the discussion, I will focus for now on the case where the diploma is the only signal (but perhaps the econometrician is not aware of this). I return to the case of multiple signals below.

The running variable for the RDD is the test score z_i, the treatment is diploma receipt as indicated by d_i, and the assignment rule is given by (3). The RDD consistently estimates the causal effect of diploma receipt on wages, or the information value of the diploma δ, provided that the distribution of innate talent does not jump at the cutoff. A sufficient condition is that workers cannot *precisely* manipulate their test score (Lee and Lemieux, 2010). This condition is satisfied thanks to the noise term in equation (1).

Why then does the RDD not help to distinguish between signalling and human capital theories of education? In terms of the model and Proposition 1, the reason is simply that the diploma has information value ($\delta > 0$) regardless of whether productivity is determined by acquired knowledge only, $a_k > 0$ and $a_\theta = 0$, which corresponds to a pure human capital theory of education; or whether acquired knowledge has no effect on productivity, $a_k = 0$ and $a_\theta > 0$, corresponding to a pure signaling view; or whether a combination of both theories holds, $a_k > 0$ and $a_\theta > 0$.

Equation (7) demonstrates that RDD, although comparing statistically identical *marginal* workers, identifies a quantity that contains information about *infra-marginal* workers (the cumulative distribution functions conditional on diploma receipt). Perhaps it is this insight that is overlooked by researchers who interpret RDD estimates of diploma effects as evidence of signaling. The implication of an RDD detecting a positive diploma information value is that employers have different beliefs about workers with diploma from those without. These differences in beliefs *must* be based on a comparison of a large number workers with diploma to a large number of workers without, and *cannot* be based on a comparison just of workers close to the threshold. Since employers do not observe test scores, they cannot make this comparison—and if they could, there would be no diploma information value. Finally, the observation that employers expect workers with diploma to have higher productivity than those without, tells us nothing about the sources of these differences in beliefs. It could be that knowledge generates human capital, of which workers who study more efficiently will accumulate more. Or, it could be that knowledge has no impact on productivity, but that study efficiency and productivity are positively correlated, hence allowing workers to signal their type through acquisition of a diploma. These issues cannot be resolved by an RDD, nor any other way of (quasi-)randomly assigning diplomas. And although quasi-experimental designs are capable of estimating diploma information values, these estimates cannot be interpreted as "net of human capital effects" (Tyler, Murnane, and Willett, 2000).

It is worth thinking about wage variation away from the cutoff more thoroughly. Clark and Martorell (2014, p284) argue that "in the broader population, the measured earnings advantage enjoyed by workers with diplomas reflects [the diploma's] signaling value plus any productivity differences that firms observe." Let us return to the case mentioned above where employers receive another noisy signal s_i about workers' type. Worker i now earns a wage $w_i = \mathbb{E}[p_i|d_i, s_i]$. In general, it is difficult to determine the functional form of this conditional expectation. A natural starting point is an additive formulation, $\mathbb{E}[p_i|d_i, s_i] = \delta d_i + g(s_i)$, where $g(\cdot)$ is some strictly increasing, continuous function. The simple mean comparison $\mathbb{E}[w_i|d_i = 1] - \mathbb{E}[w_i|d_i = 0]$ now delivers $\delta + \mathbb{E}[g(s_i)|d_i = 1] - \mathbb{E}[g(s_i)|d_i = 0]$, which overstates the diploma information value since innate talent is positively correlated with both diploma receipt and the second signal. However, by comparing workers close to the threshold, an RDD is capable of recovering δ.[12] In general, we may have $\mathbb{E}[p_i|d_i, s_i] = h(d_i, s_i)$, where $h(\cdot, \cdot)$ is *not* additive in the two signals. The information value of the diploma will then not be constant, and a standard RDD will deliver a local estimate instead.[13] In any case, the substantive point is that wage variation around the cutoff comes from the diploma signal; wage variation away from the cutoff, and conditional on diploma receipt, is due to separate information about workers' types that employers receive; and wage differences by diploma status in the whole population reflect both the diploma signal and the separate information. Again, this is true regardless of whether the labor market is described by a pure signaling model, or by a human capital model.

[12] Of course, implementation of an RDD requires dealing with the relationship between wages and test scores away from the cutoff, for instance using local polynomials.

[13] It is possible to extrapolate RDD treatment effects in some circumstances, as shown by Angrist and Rokkanen (2015).

5 Both signaling and human capital will produce zero RDD estimates for wages in the long run if ability is revealed over time, and RDD can be used to estimate the speed of learning

In this section I explore how RDD can contribute to our understanding of employer learning. I first take the model of Sections 2 and 3 and modify it to allow for learning. Leaving that model behind, I then consider a more general framework.

To analyze the role of learning in the model of the previous sections, let us add a second period of production to the model. At the end of the first period, workers' ability is fully revealed. This means that in the second period, all workers are paid their true marginal product p_i. Since innate talent, and hence knowledge, vary continuously around the threshold for diploma receipt, an RDD using second-period wages will estimate a zero effect. Because workers' ability has been revealed, the diploma loses its information value. Once more, this holds regardless of the relative importance of signaling and human capital.

Now consider a more realistic framework in which productivity may be time-varying. Let individual i's productivity at time t be given by

$$p_{it} = \pi(\theta_i, t). \tag{8}$$

The function π is assumed to be constant across individuals and over time, and continuous in its arguments. These arguments include the time-invariant worker trait θ_i, where we assume as before that such innate talent may influence productivity directly or indirectly through acquired human capital; and time t reflecting productivity growth due to further human capital investments such as on-the-job training as well as any aggregate labor productivity growth. The two arguments may interact, so that differences in innate talent may lead to differences in productivity growth. Employers know the function π.

Note that I omit knowledge k from (8) to save on notation. In terms of the model of Section 2, its effects are of course captured by the presence of θ given the one-to-one mapping between innate talent and knowledge. The distinction between direct productivity effects of θ, and indirect effects through k, is not essential here.

Equation (8) is a generalization of productivity processes typically assumed in the employer learning literature, see for instance equation (2) in Lange (2007).[14] It implies that true productivity is independent of past productivity realizations, as well as past wages, conditional on θ_i and t. I discuss the plausibility of these assumptions below. For now, let us simply observe that they are in line with the employer learning literature. (To be sure, expectations of productivity formed by employers are of course assumed to depend on past productivity in this literature.)

Given risk neutrality of employers and workers, wages equal the expected value of productiv-

[14] Note that θ could be a vector rather than a scalar.

ity according to the employers' beliefs, $w_{it} = \widehat{\mathbb{E}}_t[p_{it}]$, which may be different from p_{it}. Indeed, let us assume that employers are initially uncertain about θ_i, and that this is the object that they learn about over time. Following the employer learning literature I assume that any new information that is revealed about individuals' productivity is known to all market participants, so that all employers share the same beliefs. The time subscript in $\widehat{\mathbb{E}}_t$ reflects the information that employers acquire over time (as well as their prior knowledge about how the conditional means change with time, see below).

Average productivity may be conditioned on whether individuals fall below or above the threshold, denoted by $\mathbb{E}[p_{it}|d_i = 0]$ and $\mathbb{E}[p_{it}|d_i = 1]$, respectively. We can similarly condition employers' beliefs, and hence we can write average wages for workers above and below the threshold as $w_{0t} = \widehat{\mathbb{E}}_t[p_{it}|d_i = 0]$ and $w_{1t} = \widehat{\mathbb{E}}_t[p_{it}|d_i = 1]$. For workers close to the threshold ('local'), we have $\mathbb{E}[p_{it}|d_i = 0, \text{local}] = \mathbb{E}[p_{it}|d_i = 1, \text{local}]$ given (8) and since θ_i does not jump at the threshold. As in the simple extension of the model, if employers have learned about workers' productivity—the time-invariant component of workers' productivity θ_i has been revealed—then $\widehat{\mathbb{E}}[p_{it}] = \mathbb{E}[p_{it}]$ and in particular $\widehat{\mathbb{E}}[p_{it}|d_i, \text{local}] = \mathbb{E}[p_{it}|d_i, \text{local}]$, hence $w_{0t}^{\text{local}} = w_{1t}^{\text{local}}$.

How fast do employers learn about worker ability? If wage data at several points in time are available, then an RDD can actually help answer this question. Estimating the speed of learning is a difficult problem because it is typically not possible to observe the mistakes that employers make when assessing workers' productivity. Lange (2007) employs an indirect approach using the insight of Altonji and Pierret (2001) that initially-unobserved (by the employer) correlates of productivity, such as IQ scores, should increase in importance in a wage equation over time, while the opposite is true for easily observed correlates such as years of schooling. Lange (2007) shows that the changes in coefficients over time is informative about the speed of learning under specific functional form and distributional assumptions. Using data from the NLSY, he estimates that employers' expectation errors—the difference between wages and true productivity—decline by 50 percent within three years.

Any estimation approach for the speed of learning of course requires there to be evidence for learning in the first place. For Lange (2007), this evidence is the agreement of his data with the predictions of Altonji and Pierret (2001). The same predictions can be applied to the diploma RDD context. Learning requires the RDD coefficients to decline over time—the diploma here takes over the role of years of schooling; and it requires the slope coefficients to increase over time—the running variable takes over the role of the IQ score. I assume from now on that we deal with data in which such evidence for learning is present. In particular, I assume that RDD coefficients are indistinguishable from zero from some point T onwards, as in Khoo and Ost (2017).

Positive diploma RDD coefficients for entry wages imply that employers initially over- (under-)predict the productivity of workers closely above (below) the threshold, on average. Thus, RDD estimates prior to ability being revealed are direct estimates of the difference between expectation errors for workers just above and just below the cutoff. Let the expectation error for individual i be defined as $e_{it} \equiv \widehat{\mathbb{E}}_t[p_{it}] - p_{it}$. Furthermore, let *average* expectation errors, conditioned on diploma status, be defined as $e_{1t} \equiv \widehat{\mathbb{E}}_t[p_{it}|d_i = 1] - \mathbb{E}[p_{it}|d_i = 1]$ and $e_{0t} \equiv \widehat{\mathbb{E}}_t[p_{it}|d_i = 0] - \mathbb{E}[p_{it}|d_i = 0]$, respectively. The diploma information value (DIV) that RDD estimates is now formally expressed as

$$\text{DIV} \equiv \widehat{\mathbb{E}}_t[p_{it}|d_i = 1, \text{local}] - \widehat{\mathbb{E}}_t[p_{it}|d_i = 0, \text{local}].$$

This equals the difference in average expectation errors for workers close to the threshold,

$$\begin{aligned} \text{DIV} &= \left\{\widehat{\mathbb{E}}_t[p_{it}|d_i = 1] - \mathbb{E}[p_{it}|d_i = 1, \text{local}]\right\} - \left\{\widehat{\mathbb{E}}_t[p_{it}|d_i = 0] - \mathbb{E}[p_{it}|d_i = 0, \text{local}]\right\} \\ &\equiv e_{1t}^{\text{local}} - e_{0t}^{\text{local}}, \end{aligned}$$

since $\mathbb{E}[p_{it}|d_i = 0, \text{local}] = \mathbb{E}[p_{it}|d_i = 1, \text{local}]$.

In the scenario where RDD coefficients are indistinguishable from zero from some point T onwards, we have $e_{1t}^{\text{local}} = e_{0t}^{\text{local}}$ for $t \geq T$. This is indicative of employers having learned workers' types θ_i and hence their true productivity: $e_{1t}^{\text{local}} = 0$ and $e_{0t}^{\text{local}} = 0$ for $t \geq T$. The dynamic RDD then measures the speed of learning simply by tracing out the time path of (differences in) expectation errors. In particular, T gives the amount of time it takes for these errors to disappear. This value is estimated without imposing functional form and distributional assumptions beyond (8).[15]

There are two important caveats to the claim that RDD can estimate the speed of learning. These concern alternative interpretations of a pattern of declining RDD coefficients and the validity of the assumptions about productivity contained in (8). I note that the two caveats are due to issues that are not unique to my framework—the existing employer learning literature faces these issues, too.

The first caveat is related to the fact that RDD coefficients estimate *differences* in expectation errors, not levels. Thus, RDD coefficients will also reach zero if employers believe, correctly or incorrectly, that there are no truly time-invariant productivity differences across individuals. Formally, $e_{0T}^{\text{local}}, e_{1T}^{\text{local}} \neq 0$, but since $\mathbb{E}[p_{iT}|d_i = 0, \text{local}] = \mathbb{E}[p_{iT}|d_i = 1, \text{local}]$, this means that $\widehat{\mathbb{E}}_T[p_{iT}|d_i = 0] = \widehat{\mathbb{E}}_T[p_{iT}|d_i = 1]$. In this scenario, employers acknowledge some persistence of individual heterogeneity across education and labor market entry, $\widehat{\mathbb{E}}_{t_0}[p_{it_0}|d_i = 0] < \widehat{\mathbb{E}}_{t_0}[p_{it_0}|d_i = 1]$, so that RDD estimates are initially positive. But employers also believe that after a certain amount of time, individuals' productivity draws are uncorrelated with their initial ones, so that

[15] One could go further by allowing productivity to be stochastic: Each individual's productivity is drawn from an idiosyncratic, time-varying distribution, whose mean is given by (8). By learning about θ_i, employers then learn about the mean of the idiosyncratic productivity distributions. Rather than differences in expectation errors, RDD estimates differences in "errors in beliefs." The result that RDD can estimate the speed of learning carries over to this more general setting. I have chosen to focus on the non-stochastic case mainly to avoid additional notation.

any early signals become uninformative eventually, and this is what produces zero RDD estimates in the long run. Empirically, this scenario could be ruled out by gathering independent evidence on the persistence of wages and (beliefs about) productivity. One possibility is to examine the slope of the running variable: mean reversion implies that the slope declines over time. But note that this would contradict my premise that the data show evidence of learning.

Second, in contradiction to (8), true expected productivity may depend on the history of productivity draws as well as on past wages, even after conditioning on time-invariant worker traits. Suppose, for instance, that human capital accumulation such as on-the-job training is affected by transitory productivity variation. If there is learning, then RDD estimates will still be zero in the long run as there are no jumps at the threshold in the parameters determining transitory productivity variation. However, the interpretation of the speed of learning will be more nuanced since the learning is now about a moving target. More problematically, past wages may affect human capital accumulation, due to liquidity constraints or because employers' training choices are based on the same information as their wage setting (Kahn and Lange, 2014). Thus, workers just above the cutoff accumulate human capital at a faster rate than workers just below, at least temporarily. With learning, the differences in investment rates disappear over time, and if human capital depreciates sufficiently fast, so do the productivity differences. The time it takes for RDD estimates to become zero (or to stabilize around some positive value, if depreciation is relatively slow) is then an upper bound to the time it would take for expectation errors to disappear in the absence of differential human capital accumulation.

6 Conclusion and discussion of alternative approaches to testing signaling theory

Regression discontinuity designs that estimate the causal effect of a diploma or similar certification on wages are useful because they can detect the existence of information frictions and statistical discrimination; because they quantify the information value of a diploma; and because they can be used to measure the speed of employer learning. However, the notion that RDDs can speak to the question of whether education produces human capital or serves a pure signaling function, does not withstand the scrutiny of a theoretical model. A positive diploma information value (or signaling value) is not evidence in favor of pure signaling, because diplomas can also have information value in a human capital model featuring asymmetric information. This conclusion applies to any setting in which diplomas are (quasi-)randomly assigned.

There are at least three viable, alternative approaches to test for the relative importance of human capital and signaling. One approach is to estimate the causal effect of schooling on productive skills such as IQ. Carlsson, Dahl, Öckert, and Rooth (2015) accomplish this by using exogenous variation in the date on which Swedish men took cognitive tests for (compulsory) military enlistment. They find that an extra ten days in school raise cognitive skills by one percent of a standard deviation, while extra non-school days have almost no effect. This contradicts the pure signaling view of education.

A second approach is to deduce additional predictions from signaling theory that are truly distinct from those of the human capital model. Bedard (2001) develops a signaling model in which some high-ability individuals face barriers to entering university. If university access is expanded, then some of the previously constrained individuals enter. As the pool of high school graduates decreases in average quality, and employers realize this, some low-skill individuals no longer find high school worthwhile. The high school dropout rate increases, a prediction that contradicts the pure human capital model. Bedard (2001) does find suggestive evidence of this in US data. It seems worthwhile to search for further distinct predictions of signaling theory, and to confront them with data.[16]

A third approach to assessing the importance of signaling has been developed in the employer learning literature. This literature documents the importance of information frictions in the labor market, but also the ability of employers to overcome these frictions through learning. Lange (2007) and Lange and Topel (2006) highlight that learning imposes limits on the importance of signaling: the faster true ability is revealed, the less time is available for recouping the educational investment. With the help of a theoretical model, one can then use estimates of the speed of learning together with estimates of the opportunity cost of schooling to bound the importance of signaling. Lange (2007) suggests that for reasonable parameter choices, the upper bound on the contribution of signaling to the observed return to schooling is smaller than 15 percent. Learning appears to be simply too fast for signaling to play an important role in education choices. By estimating the speed of learning, diploma RDDs—and other strategies for isolating quasi-random variation in labor market signals—could potentially make a contribution to the signaling versus human capital debate, after all, albeit perhaps in a different way than originally intended.

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[16]In a similar spirit, Lang and Kropp (1986) argue that in a signaling model, increases in the compulsory schooling age will shift the entire distribution of schooling. They do find evidence of such a 'ripple effect' in US data. However, Lange and Topel (2006) suggest that increases in the compulsory schooling age may reflect secular increases in the value of education, which would produce the same patterns in the data.

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