

# Reconsidering the Mechanisms of Peer Achievement Spillovers: Implications for Identification and Policy\*

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## PRELIMINARY AND INCOMPLETE

### Abstract

The literature largely recognizes a role for peer achievement spillovers in educational production, though the theory behind this is not always clear. I compare two theories for why peer achievement may affect an individual's achievement, as a proxy for unobserved peer ability or effort. While the literature does not tend to distinguish between these mechanisms, I show that the implications for identification are quite different. In fact, I argue that the evidence for contemporaneous effort-type spillovers is compelling and that the tendency to focus only on spillovers from predetermined characteristics of students may be misguided. The model also helps to clarify the interpretation of spillovers from peer characteristics. I show that the marginal effect of peer characteristics may actually differ in sign depending on the underlying mechanism of peer influence. Finally, I discuss the relevance of these results for policy, particularly focusing on optimal grouping.

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# 1 Introduction

The literature on peer effects in achievement production seeks to determine how changing the composition of peer groups affects achievement. Based in the larger social interactions literature, peer effects in achievement production are divided into two categories—*endogenous* effects deriving through peer achievement and *exogenous* effects deriving through peer characteristics. Manski (1993) first recognized the inherent difficulty of separately identifying these two types of effects, and thus determining the causal mechanism of peer influence, which he coined the *reflection problem*. Yet, in the education context, frequently the reflection problem is considered to be of secondary importance next to the problem of distinguishing a *social effect* (combination of endogenous and exogenous effects) from unobserved correlated effects, such as teacher quality or selection into “like” peer groups, that may cause students in the same peer group to perform similarly.

At least two reasons are offered for ignoring the reflection problem in the education context. First, contemporaneous spillovers are either trivial or non-existent, removing the simultaneity problem. Implicitly, this suggests that estimates of the social effect in the linear-in-means model, if distinguishable from unobserved group effects, can be interpreted as causal. Second, optimal groupings may not depend on determining the causal link between peers and outcomes, but rather it may be sufficient to know that, for example, having lower-income peers is negatively correlated with achievement. Differentiating between the endogenous and exogenous effects that lead to this correlation may be of secondary importance, simply because the object of manipulation by policy makers is observable peer group composition. Again, the key here is separately identifying a social effect from unobserved correlated effects, not addressing the reflection problem. In this paper, I discuss each of these points in turn, suggesting that the tendency to minimize the importance of the reflection problem in the education context may be misguided.

I begin by formalizing some of the intuition that underlies the inclusion of peer achievement in the educational production function, in the particular context where performance is measured on annual standardized exams. I contrast two existing hypotheses—that peers affect achievement through unobserved characteristics, such as ability, and unobserved behaviors, such as effort or motivation. The important distinction for identification is that the reflection problem in reality only applies when peer achievement effects derive through the behavioral channel. Otherwise, peer achievement effectively proxies for predetermined char-

acteristics, or an unobserved exogenous effect, which can be captured by lagged values of peer achievement, the specification often chosen in the literature. Because treating peer effects as deriving solely through predetermined peer characteristics is inconsistent with much of the underlying theory and empirical evidence for peer effects, I argue that contemporaneous peer achievement is important. Therefore, the reflection problem applies to the achievement context.

Explicitly modeling the source of endogenous spillovers in achievement in turn serves as a starting point for clarifying how to interpret estimates of exogenous peer effects, adding yet another layer to the reflection problem. Conditional on a given level of peer achievement (contemporaneous or lagged), “better” peer characteristics actually predict a lower level of peer effort or ability. Thus, estimates of the exogenous effect pick up the direct effect of peer characteristics net of an indirect effect deriving through the effort channel. In the extreme, the resulting peer spillover estimates may contradict intuition suggesting that if individual characteristics, such as parental education, are positively correlated with achievement, then having more peers with those characteristics will positively (or at least non-negatively) affect achievement. In the more mild cases, the opposing channels of direct and indirect spillovers from peer characteristics may lead us to understate the exogenous effects or erroneously conclude that exogenous effects do not exist.

While the interpretation of exogenous peer effects is similar across peer effort and ability spillovers, the implications for identification and policy are quite different. When individuals are treated as utility-maximizing agents, the achievement production function can be recast as an achievement best response function. Because students choose effort as a best response to their peers, this in turn presents the possibility of an exclusion restriction that would shift an individual’s achievement independently of peers and separately identify the endogenous from the exogenous effects. This intuition cannot be extended to the peer ability case.

From the policy perspective, an important distinction between effort and ability spillovers is that only the former generates social multiplier effects. With social multipliers, estimating the effect of reallocating resources from higher-achievers to lower-achievers (a potential consequence of the No Child Left Behind Act) must take into account the spillover generated from increased performance of low-achievers to their peers. However, in other settings, the policy maker may simply want to know how the reallocation of students based on observable characteristics affects achievement. For instance, does desegregating classrooms improve the achievement of nonwhite students? Does the cream-skimming that is a potential consequence

of increased school choice benefit high achievers at the expense of low-achievers? This provides a context where estimates of the social effect may be sufficient to determine the effects of altering peer group composition, therefore making it unnecessary to distinguish between the alternative channels of peer influence.

In particular, because the literature on the effects of desegregation is vast and evidence is mixed, I focus the discussion on racial composition effects. I begin by considering whether estimates of the unconditional correlation between racial composition and achievement, the total “social effect”, are sufficient for determining the effect of desegregation. I focus on the “best case” scenario of the linear-in-means model which imposes common treatment effects across students, noting that causal estimates are likely to take on even more importance in the context where there are heterogeneous treatment effects. Because the linear-in-means model predicts no effect on average achievement of the population from regrouping students, I consider the effect on average white and black achievement and the associated achievement gap.

Not surprisingly, the applicability of the reduced form estimates depends critically on the question of interest and the context in which the reallocation is implemented. A pervasive problem in the literature is how to deduce estimates of the racial composition effect when there is matching between students and teachers. I show that even if it is possible to obtain consistent estimates of the racial composition parameter without random assignment, for instance through within-school estimates, these estimates cannot be used to determine the effects of desegregation across schools. Because any large scale reallocation involves reassignment of students to teachers, estimates of the endogenous effect parameter (i.e., the social multiplier associated with the new teacher assignment) are necessary to determine the new equilibrium achievement.

While the intuition above suggests that introducing peer achievement into the production function biases estimates of the exogenous effect toward zero, separating race from “ability” effects may be important for policies such as determining the effect of shifting from integration based on race to race-blind policies that integrate based on measures of prior achievement. Therefore, I also consider the extent to which estimates of exogenous effect conditional on prior peer achievement, in the absence of a causal interpretation, can be applied to these policy questions.

## 2 Sources of Peer Achievement Spillovers

In other branches of the social interactions literature, the potential importance of endogenous effects for determining behavior is relatively self evident. Consider for instance the decision of a teenager to smoke or drink alcohol. Few would argue that the tendency toward such behaviors is unaffected by peer pressure, i.e., by having peers that engage in these behaviors. Yet, the role endogenous effects play in achievement is less clear, and this has led to considerable confusion regarding peer spillovers in the achievement production context. Annual standardized exams are often the outcome of interest, and, in the absence of cheating, are not a group effort. Thus, peer achievement per sé may not affect a student’s achievement, as discussed by [Hanushek et al. \(2003\)](#) and others.

Yet, despite this observation, some measure of peer achievement is generally included among the potential peer effects in the achievement production function and is frequently even the input of interest. Why is this? In reality, peer achievement may signal something about peers that affects achievement production. There are several theories underlying the inclusion of peer achievement as an input to production. I distinguish between two—one that treats peer achievement as capturing unobserved characteristics of the student (such as ability) and another as capturing an unobserved action or behavior of the student (such as effort). Generally effort and ability are thought to be highly correlated, but in one of the few studies that attempts to link studying to academic performance, [Stinebrickner and Stinebrickner \(n.d.\)](#) show that ability is not generally a good predictor of effort. Theoretically, the distinction between peer ability and peer effort spillovers is likely to be important both for identification and policy, as discussed in Sections 4 and 5 respectively.

In the ability case, achievement is not affected by contemporaneous behaviors but rather by predetermined characteristics, and the difficult simultaneity issues at the core of the reflection problem need not apply. In contrast, when students’ actions are important, the effort case, the reflection problem becomes central to understanding peer effects. While the literature generally refers to both types of spillovers as “endogenous” peer effects, the peer ability spillover can be more correctly characterized as an *unobserved exogenous effect*. Therefore, I attempt to restrict the use of the term *endogenous* peer effects in this paper to those arising from contemporaneous peer spillovers.

To put some structure on the problem, let  $i$  index the individual student,  $g$  the peer

group, and  $t$  the academic year. Let  $Y_{igt}$  denote achievement on a standardized exam, which is taken at the end of each academic year. The observed individual characteristics that affect achievement production are  $X_{it}$  and often include parental education, race, sex, and some measure of income. Students also differ in an unobserved characteristic  $A_{it}$ , which is referred to as ability. The time index permits the treatment of ability in terms as accumulated human capital, rather than just innate ability. Behavior or actions ( $e_{igt}$ ) can also affect achievement. I loosely term this choice as “effort,” but it is intended to denote a wide range of behaviors that are more or less conducive to achievement, such as working hard in class, asking more or less productive questions, misbehaving or distracting classmates, or cooperating in group work. The production function may also include peer characteristics ( $\bar{X}_{gt}$ ), peer ability ( $\bar{A}_{gt}$ ) and peer effort ( $\bar{e}_{gt}$ ), and I assume that it is the mean that matters, as denoted by the bar. Finally, observed peer group level inputs ( $K_{gt}$ ), such as teacher experience or expenditure, and unobserved inputs ( $\mu_{gt}$ ), such as unobserved teacher quality, can affect achievement.

The structural achievement production function can then be written as

$$Y_{igt} = X_{it}\alpha_1 + \bar{X}_{gt}\alpha_2 + K_{gt}\alpha_3 + \alpha_4(A_{it} + \sigma_1 e_{igt}) + \alpha_5(\bar{A}_{gt} + \sigma_2 \bar{e}_{gt}) + \mu_{gt} + \epsilon_{igt}, \quad (2.1)$$

$$= X_{it}\alpha_1 + \bar{X}_{gt}\alpha_2 + K_{gt}\alpha_3 + \alpha_4 u_{igt} + \alpha_5 \bar{u}_{gt} + \mu_{gt} + \epsilon_{igt} \quad (2.2)$$

where  $\epsilon_{igt}$  captures either measurement error or random shocks to achievement. For achievement to be a valid proxy for either effort or ability requires imposing a monotonicity assumption, i.e., that  $\alpha_4 > 0$  and  $\sigma_1 > 0$ . For expositional purposes, equation (2.2) imposes the somewhat restrictive assumption that  $\sigma_1 = \sigma_2$ , so that the unobserved peer effect is just the average of  $u_{igt}$ . This assumption is relaxed in later sections. Because of the connection between the unobserved individual and peer effect, much of the intuition below begins with an interpretation of the individual effect.

For the moment, I take observable exogenous peer effects,  $\bar{X}_{gt}$ , they are discussed more carefully in Section 3. Note that generally peer spillovers are measured exclusive of  $i$  rather than the average inclusive of  $i$  as used here. Given sufficiently large peer groups, the distinction should not make much of a difference in practice, but complicates the algebra considerably. Therefore, for expositional purposes I stick to the mean inclusive of  $i$ . Furthermore, though the linear-in-means form of production abstracts from some interesting policy implications, it provides a simple starting point for comparison to previous results in the literature.

I assume that a parameter of interest is the unobserved peer effect,  $\alpha_5$  and/or  $\alpha_5\sigma_2$ . Knowledge of this effect is particularly important for understanding the costs and benefits of academic tracking or the potential “cream-skimming” effects of high-achievers associated with increased school choice. The challenge is to estimate these parameters without direct knowledge of  $\bar{u}_{gt}$ . Of course, this discussion is moot if there are no unobserved peer effects, or  $\alpha_5 = 0$ . However, a large literature on peer effects in achievement production suggests that this is not the case,<sup>1</sup> so I assume that  $\alpha_5 \neq 0$ .

Because the trend in the literature is to minimize the importance of contemporaneous peer spillovers, below I consider assumptions that permit the treatment of the unobserved peer effect as either predetermined or a fixed effect, effectively permitting the use of lagged values of achievement as a proxy.

## 2.1 Contexts where Prior Achievement is Valid Proxy

### 2.1.1 Unobservable as fixed effect

The following set of conditions would justify treating  $u_{igt}$  as a fixed effect:

- (i.)  $A_{it} = A_i$  for every  $t$ , and either
- (ii.)  $e_{igt} = e_{igt-1}$  for all  $g$  and  $t$ , or
- (iii.)  $\sigma_2 = 0$ .

Assumption (i) holds if only innate ability matters for achievement. The implication of no human capital accumulation is unappealing given that this is the very purpose of schooling. In addition, we must impose either Assumption (ii) or (iii). Assumption (ii) holds if individuals exert the same effort every year, i.e., they do not change their behavior based on teacher characteristics, peers, or other inputs. In this case, it is not useful to distinguish between ability and effort, and we could similarly assume that effort is an unobserved characteristic or peer effort does not matter ( $\sigma_2 = 0$ ), Assumption (iii). These assumptions further imply that any change in achievement from year to year, after conditioning on observables and

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<sup>1</sup>For instance, see Cooley (2006), Graham (2004), Hanushek et al. (2003), Sacerdote (2001), Vigdor and Nechyba (forthcoming), among others.

individual and peer fixed effects, are due to random variation or changes in teacher quality  $\mu$ . Therefore, I term this the *passive* model of student achievement.

Given that Assumptions (i) and (ii) or (iii) hold, then  $u_{igt} = u_i$  and  $\bar{u}_{gt} = \bar{u}_g$ . Therefore, average peer achievement may serve as a viable proxy for  $\bar{u}_g$  under the maintained monotonicity assumption. Because the unobserved effect is fixed, lagged values may also be used as proxies, the approach frequently taken in the literature.

***What about the value-added specification?*** In reality, the literature recognizes that achievement is more intuitively conceived as a cumulative learning process, in which students accumulate human capital as they progress through school.<sup>2</sup> Thus, a value-added specification is generally the preferred method of capturing the learning process, i.e.,

$$Y_{igt} = \delta Y_{igt-1} + X_{it}\alpha_1 + \bar{X}_{gt}\alpha_2 + K_{gt}\alpha_3 + \alpha_4 u_{igt} + \alpha_5 \bar{u}_{gt} + \epsilon_{igt}. \quad (2.3)$$

In this case, Assumption (i) does not negate the process of human capital accumulation but suggests rather that an individual's achievement gains are determined by his innate ability and not by prior learning. Assumptions (ii) and (iii) retain the same interpretation, where learning is conceived in terms of gains rather than levels. Therefore, conditions that make  $u_{igt}$  interpretable as a fixed effect have similar implications, that the school and teacher and peers, for that matter, cannot affect the student's capacity or desire to learn.

Because of concerns about unobserved correlated effects ( $\mu_{gt}$ ), which may determine both the lagged value of the achievement of an individual and his peers, generally twice-lagged peer achievement is used as a proxy for the unobserved peer effect in the value-added context. As an aside, this suggests that thrice-lagged peer achievement should also be included in the value-added specification, i.e.,  $\bar{u}_g$  is captured by  $\frac{1}{\alpha_4 + \alpha_5}(\bar{Y}_{gt-2} - \delta \bar{Y}_{gt-2} - \dots)$ . Because the distinction does not affect the central conclusions of this paper, most of the analysis centers around the contemporaneous specification for simplicity, though I do contrast results with the value-added specification when appropriate.<sup>3</sup>

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<sup>2</sup>See, for instance, [Todd and Wolpin \(2003\)](#).

<sup>3</sup>[Todd and Wolpin \(2003\)](#) provide a careful discussion of the relative merits of the contemporaneous and value-added specifications as described in equations (2.1) and (2.3) here.

### 2.1.2 Time-varying, but predetermined unobservable

Using lagged values of peer achievement to proxy for the unobserved peer effects, while arguably appropriate given the fixed effect interpretation, may still work under weaker timing assumptions. For instance, suppose we maintain the passive model of student achievement, but allow the unobserved individual effect to be time varying,  $u_{igt} = u_{it}$ . In words, the unobservable does not depend on the current peer group but may vary over time due to some process such as human capital accumulation. Therefore Assumptions (i)-(iii) are modified such that

(i'.)  $A_{it} = \delta_1 A_{it-1}$  for every  $t$ , and either

(ii'.)  $e_{igt} = e_{it} = \delta_2 e_{it-1}$  for all  $g$  and  $t$ , or

(iii'.)  $\sigma_1 = \sigma = 0$ .

Given Assumptions (i) and (ii), the individual effect can be written as  $u_{igt} = u_{it} = \delta_1 A_{it-1} + \delta_2 \sigma e_{it-1}$  and  $\bar{u}_{gt} = \delta_1 \bar{A}_{gt-1} + \delta_2 \sigma \bar{e}_{gt-1}$ .

To emphasize, the timing assumption is that inputs up to the prior Spring matter in determining the unobserved individual effect, but contemporaneous inputs from Fall to Spring of the current year do not.<sup>4</sup> Thus, peer effects during the academic year derive only through predetermined characteristics. While ability is easily perceived as cumulative, effort may be less so. However, a model where habit persistence dominates may suggest a process similar to that described here. In this case, the lagged value of peer achievement would be the appropriate proxy for capturing  $\bar{u}_{gt}$ . The underlying assumption again is that individual students do not influence each other directly in terms of unobservables, but rather that there is something about having a group that is innately better (i.e., peers that have accumulated more knowledge) for achievement.

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<sup>4</sup>In a higher frequency context, where multiple test outcomes are observed within a particular academic year for a given class, this distinction is likely to be less stark. However, prior test scores (i.e., in same grade or class and year) no longer provide a solution for the unobserved correlated effects given the students are exposed to the same set of inputs throughout the year. In other words, the timing assumption in this higher frequency environment has no bite for identification.

## 2.2 Effort spillovers

In contrast with the conditions described above, many models of achievement implicitly assume that students respond to the classroom environment, their teachers and potentially peers. A student might work harder with certain teachers and less with others, simply depending on how much the teacher stimulates him to think or how much he respects the teacher. The implication is that the above conditions may not hold, and that in fact contemporaneous spillovers are important. Below, I briefly consider some existing evidence in the literature.

First, several studies have found support for a [Lazear \(2001\)](#)-type model of peer influence, where the disruptive behavior of a student imposes negative externalities on other students in the classroom. For instance, both [Figlio \(2003\)](#) and [Kinsler \(2006\)](#) present empirical evidence that disruptive peers negatively affect achievement.

Second, the debate over academic tracking largely centers around whether the purported gains from homogeneous classes with a more targeted curriculum can offset the potential losses to low-achievers from being grouped with other low-achievers. The negative side effects are generally not merely lower ability peers per se, but rather decreased motivation, lower expectations, and discouragement, all of which are of the time-varying effort type. Evidence also suggests that more time is allocated in lower-track classes to discipline, suggesting potentially negative spillover effects from these types of academic disengagement.<sup>5</sup>

One final example is evidence regarding a social stigma attached with high achievement among black students, labeled the “burden of acting white” in the literature.<sup>6</sup> The evidence is suggestive of peers playing a role in setting norms which are more or less conducive with achievement. For instance, [Fryer and Torelli \(2005\)](#) find evidence that higher academic achievement is more strongly associated with popularity for whites than for blacks. [Austen-Smith and Fryer \(2005\)](#) provide a theoretical model of this effect, with the clear underpinning being that peers matter in setting norms of student behavior.

Given the theoretical and empirical evidence supporting behavioral spillovers, I argue that the tendency to ignore contemporaneous peer spillovers in achievement production is misguided, leading researchers to severely understate the importance of the reflection

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<sup>5</sup>See [Hallinan \(1994\)](#) for a discussion and [Rosenbaum \(1976\)](#) and [Oakes \(1985\)](#) for field evidence.

<sup>6</sup>See [Fordham and Ogbu \(1986\)](#) among others.

problem. I briefly develop the implications for policy in Section 5.

The above arguments are based on the assumption that peer achievement itself does not matter for production. In a context where we are considering only direct externalities of peers on achievement production this seems justified, i.e., the externalities are coming through behaviors rather than achievement. In contrast, when students are treated as optimizing agents and choose behaviors based on peers, as suggested in the tracking and acting white literature, there may be a direct role for prior peer achievement in determining effort. For instance, if students are placed with peers who are higher performing, as they observe through knowledge of prior achievement, they could choose to work harder to maintain a certain status in the class. However, as long as this is accompanied by direct externalities from peer effort on production or responses to peer effort, the treatment of peer achievement as a proxy for unobservable peer characteristics remains important.

### 3 Interpreting Exogenous Peer Effects in the Context of a Structural Model

As discussed in the previous section, the literature generally takes as a starting point that peer achievement belongs in the achievement production function, i.e., achievement can be written as

$$Y_{igt} = X_{it}\gamma_1 + \bar{X}_{gt}\gamma_2 + K_{gt}\gamma_3 + \gamma_4\bar{Y}_{gt} + \xi_{igt}. \quad (3.1)$$

I term this equation the semi-structural equation, to distinguish it from the structural equation (2.1), which explicitly recognizes the source of peer achievement spillovers as deriving through one or both of the unobservable channels. In this section, I focus particularly on the implications of treating the “endogenous” peer effects as arising through unobservables for the interpretation of the exogenous peer effects,  $\gamma_2$ .

Generally the intuition is that if a characteristic is beneficial to achievement (i.e.,  $\gamma_1 > 0$ ), then the effect of having more peers with that characteristic should also be positive, or at least non-negative. However, estimates in the literature do not always bear out this intuition.<sup>7</sup> For instance, Hanushek et al. (2003) find that having more peers receiving free/reduced price lunch is positively correlated with achievement, conditional on twice-

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<sup>7</sup>For instance, see Table 1

lagged peer achievement. Cooley (2006) finds that having peers with better-educated parents is negatively correlated with achievement controlling for contemporaneous peer achievement.

While the previous section discusses the potential importance of contemporaneous peer spillovers, I begin by explicitly modeling the ability spillover case, treating students as passive inputs to the achievement process. This provides the clearest exposition of the implications for interpreting exogenous peer effects in the context where peer achievement is proxying for an unobservable. I then turn to the peer effort case in Section 3.2. The model is considerably more involved and while the implications for exogenous peer effects are similar, the contrast is important for identification.

### 3.1 Ability Model

To simplify notation, I suppress peer group and time subscripts and focus on a particular peer group, such as a class, in a particular time period. I rewrite the structural production function (2.1) as

$$Y_i = X_i\alpha_1 + \bar{X}\alpha_2 + \tilde{K}\alpha_3 + \alpha_4A_i + \alpha_5\bar{A} + v_i, \quad (3.2)$$

where  $v_i \equiv \alpha_6e_i + \alpha_7\bar{e} + \epsilon_i$  and  $\tilde{K} \equiv (K, \mu)$ . This is slightly more general than equation (2.1), which imposes that  $\alpha_6 = \sigma_1\alpha_4$  and  $\alpha_7 = \sigma_2\alpha_5$ . Ability is unobserved to the econometrician, so peer achievement is used as a proxy. I assume that achievement is monotonically increasing in ability, i.e.,  $\alpha_4 > 0$ , so that achievement provides a good proxy for ability. Solving for average peer ability as a function of peer achievement and other inputs and substituting for peer ability in equation (3.2) yields

$$\begin{aligned} Y_i &= X_i\alpha_1 + \bar{X} \left( \alpha_2 - \frac{(\alpha_1 + \alpha_2)\alpha_5}{\alpha_4 + \alpha_5} \right) + \tilde{K}\alpha_3 \left( 1 - \frac{\alpha_5}{\alpha_4 + \alpha_5} \right) + \alpha_4A_i + \frac{\alpha_5}{\alpha_4 + \alpha_5}\bar{Y} + \left( v_i - \frac{\alpha_5}{\alpha_4 + \alpha_5}\bar{v} \right) \\ &\equiv X_i\tilde{\gamma}_1 + \bar{X}\tilde{\gamma}_2 + \tilde{K}\tilde{\gamma}_3 + \tilde{\gamma}_4\bar{Y} + \tilde{\gamma}_5A_i + v_i - \tilde{\gamma}_4\bar{v}. \end{aligned} \quad (3.3)$$

The question of interest is how to interpret the exogenous effects parameter,  $\tilde{\gamma}_2$ . First, note that as long as  $\alpha_5 \geq 0$ , the endogenous effects parameter  $\tilde{\gamma}_4 \in [0, 1)$ .

Suppose further that there is no direct effect of peer characteristics on achievement, so that  $\alpha_2 = 0$  and  $\tilde{\gamma}_2 = -\alpha_1\tilde{\gamma}_4$ . Given  $\alpha_1 \neq 0$  and  $\alpha_5 > 0$ , the exogenous peer effect still enters the achievement production function but takes on the opposite sign of the individual effect  $\alpha_1$ .

A particular example of an exogenous effect may help clarify. Suppose we consider the effect of parental education. The literature generally supports the finding that students with better-educated parents perform better in school on average. This could follow if for instance better-educated parents value education more and are more able or more willing to spend time teaching their child outside of the classroom, helping on homework assignments, and facilitating other activities conducive to achievement.

But, what is the rationale for an effect of the parental education of peers on achievement? At one level, parents are not in the classroom and therefore cannot directly affect achievement production. Yet, peer parental education could potentially affect the productivity of the teacher, for instance, if better-educated parents spend more time monitoring and this has positive spillovers for the classroom. However, conditional on a given set of teacher inputs, it is more difficult to come up with a rationale for direct spillovers from peer parental education in the classroom. Therefore, this suggests a setting where it would not be surprising to find a negative effect of peer parental education on achievement, simply because the peer characteristic enters indirectly (and thus negatively) as a proxy for peer ability.

If there are direct spillovers from peer characteristics in achievement production,  $\tilde{\gamma}_2$  has the predicted sign of  $\alpha_2$  if  $\frac{\alpha_2}{\alpha_1} \geq \frac{\tilde{\gamma}_4}{1-\tilde{\gamma}_4}$ . Again the sign of  $\tilde{\gamma}_2$  in this simple model is indeterminate because of the countervailing influences of the indirect effect of peer characteristics as proxying for unobserved peer ability and the direct effect of peer characteristics in achievement production. If own characteristics play a dominant role in achievement production, i.e.,  $\alpha_1 > \alpha_2$ , a necessary condition is that  $\tilde{\gamma}_4 < .5$ , which is true for most estimates of peer ability spillovers. Intuitively, this suggests that the stronger the spillovers from peer ability, the stronger the direct effect of the individual characteristic, and the weaker the direct effect of peer characteristics, the more likely  $\tilde{\gamma}_2$  is to take a “counterintuitive” sign.

It is important to note that when peer groups do not change over time and characteristics are time invariant, the same argument holds when lagged peer achievement is used to proxy for peer ability. The intuition further applies when peer groups are varying over time, though the negative indirect effect may be weaker. This is because the individual effect still enters negatively as a predictor of peer ability but the negative peer characteristic effect may be weaker due to changes in peer groups.

## 3.2 Effort Model

I now turn to a model that explicitly treats students as decision-makers and provides a starting point for interpreting the semi-structural production function in equation (3.1) as arising from a model of peer effort spillovers. To do so, requires imposing fairly strict functional form assumptions on both utility and achievement production in order to obtain an achievement equation that is linear-in-means, both in peer achievement and characteristics.<sup>8</sup>

The model also serves to solidify the intuition developed in Section 2 regarding the potential importance of contemporaneous peer spillovers. In particular, I discussed at least two ways that the literature provides support for peer effort-type spillovers to achievement. The Lazear-type model suggests a role for peer effort as a direct input into the achievement production function, i.e., disruptive peers detract from the learning environment with negative consequences to achievement. Peers are also likely to play a role in setting norms of conduct that may provide social pressures against or in favor of high achievement.<sup>9</sup> While either is sufficient to motivate endogenous peer effects, I permit both types of spillovers in the model described below.

I assume that the utility for student  $i$  can be written as

$$U_i = \beta_1 Y_i - \frac{\beta_2}{2} e_i^2 + \beta_3 e_i \bar{e},$$

where  $\beta_1 \geq 0$ ,  $\beta_2 \geq 0$ ,  $\beta_3 \geq 0$ . Students derive utility from achievement, and there is a cost to effort. However, the cost of effort is diminishing in the average effort of peers, what Brock and Durlauf (2001) term the *proportional spillovers* case. Intuitively, this picks up the notion that there are costs to deviating from the norm (the average behavior of the peer group). To provide a familiar example in the context of achievement, the cost of working hard in a class of non-hard-working peers is likely to be much larger because the student risks standing out as a “nerd” or “teacher’s pet.”<sup>10</sup>

The achievement realized by student  $i$  is a function of his own effort, the effort of his peers, and other exogenous inputs, i.e.,

$$Y_i = X_i \alpha_1 + \bar{X} \alpha_2 + \tilde{K} \alpha_3 + \alpha_4 A_i + \alpha_5 \bar{A} + \alpha_6 e_i + \alpha_7 \bar{e} + \epsilon_i. \quad (3.4)$$

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<sup>8</sup>Cooley (2006) develops a more general form of this model.

<sup>9</sup>See Bishop et al. (2003).

<sup>10</sup>For instance, see Bishop et al. (2003).

In order to specify the effort chosen by students, it is necessary to define the student's information set. I assume that students observe  $\{X_i, \bar{X}, A_i, \bar{A}, \tilde{K}\}$  when choosing effort, whereas  $(\epsilon_1, \dots, \epsilon_N)$  are unobserved by  $i$  and his peers.<sup>11</sup> Thus, I am assuming a game of incomplete, but symmetric information. Students possess a common prior on the distribution of the random shock,  $f(\epsilon_i|X_i, \bar{X}, A_i, \bar{A}, \tilde{K})$ , which is assumed to be mean 0. A student  $i$ 's expected utility from a given level of effort and peer effort is then

$$\begin{aligned} E(U_i|X_i, \bar{X}, A_i, \bar{A}, \tilde{K}, e_i, \bar{e}) &= \beta_1 E(Y_i|X_i, \bar{X}, A_i, \bar{A}, \tilde{K}, e_i, \bar{e}) - \frac{\beta_2}{2} e_i^2 + \beta_3 e_i \bar{e}, \\ &= \beta_1 \left( X_i \alpha_1 + \bar{X} \alpha_2 + \tilde{K} \alpha_3 + \alpha_4 A_i + \alpha_5 \bar{A} + \alpha_6 e_i + \alpha_7 \bar{e} \right) - \frac{\beta_2}{2} e_i^2 + \beta_3 e_i \bar{e}. \end{aligned}$$

Students simultaneously choose effort to maximize expected utility. Therefore, student  $i$ 's best response to any given level of average peer effort can be described as

$$e_i^{BR} = \frac{\beta_1 \alpha_6}{\beta_2} + \frac{\beta_3}{\beta_2} \bar{e}.$$

Utility-maximizing effort is a function of the marginal utility of effort relative to the cost and is increasing in the average effort of peers as a result of the conformity effect.<sup>12</sup>

Assuming  $\alpha_6 > 0$  so that achievement is monotonically increasing in effort, the effort best response maps into an achievement best response, which is observable to the econometrician. Solving for average peer effort as a function of achievement using the production function in (3.4), we have

$$\bar{e} = \frac{1}{\alpha_6 + \alpha_7} \left( \bar{Y} - \bar{X}(\alpha_1 + \alpha_2) - \tilde{K} \alpha_3 - \bar{A}(\alpha_4 + \alpha_5) - \bar{e} \right).$$

We can then rewrite the effort best response as a function of average peer achievement, i.e.,

$$e_i^{BR} = \frac{\beta_1 \alpha_6}{\beta_2} + \frac{\beta_3}{\beta_2} \frac{1}{\alpha_6 + \alpha_7} \left( \bar{Y} - \bar{X}(\alpha_1 + \alpha_2) - \tilde{K} \alpha_3 - \bar{A}(\alpha_4 + \alpha_5) - \bar{e} \right).$$

Plugging  $i$ 's best response into the achievement function, we have the achievement best

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<sup>11</sup>This may also include any unobservable aspect of ability.

<sup>12</sup>Note that allowing for effort and peer effort complementarities in the achievement production function would suggest that the best response is increasing in average peer effort even in the absence of the conformity effect.

response as

$$\begin{aligned}
Y_i^{BR} &= \frac{\alpha_6^2 \beta_1}{\beta_2} + X_i \alpha_1 + \bar{X} \left( \alpha_2 - \frac{\beta_3 \alpha_6 + \beta_2 \alpha_7}{\beta_2 (\alpha_6 + \alpha_7)} (\alpha_1 + \alpha_2) \right) + \tilde{K} \alpha_3 \left( 1 - \frac{\beta_3 \alpha_6 + \beta_2 \alpha_7}{\beta_2 (\alpha_6 + \alpha_7)} \right) + A_i \alpha_4 \\
&\quad + \bar{A} \left( \alpha_5 - \frac{\beta_3 \alpha_6 + \beta_2 \alpha_7}{\beta_2 (\alpha_6 + \alpha_7)} (\alpha_4 + \alpha_5) \right) + \frac{\beta_3 \alpha_6 + \beta_2 \alpha_7}{\beta_2 (\alpha_6 + \alpha_7)} \bar{Y} + \epsilon_i - \frac{\beta_3 \alpha_6 + \beta_2 \alpha_7}{\beta_2 (\alpha_6 + \alpha_7)} \bar{\epsilon}, \\
&\equiv \gamma_0 + X_i \gamma_1 + \bar{X} \gamma_2 + \tilde{K} \gamma_3 + \gamma_4 \bar{Y} + \gamma_5 A_i + \gamma_6 \bar{A} + \epsilon_i - \gamma_4 \bar{\epsilon}.
\end{aligned}$$

Given that the achievement best response is linear-in-parameters, it can be shown that a unique Nash equilibrium exists to this game,  $(Y_1^*, \dots, Y_N^*)$ . The observed equilibrium achievement as a function of individual and peer characteristics can then be written as

$$Y_i^* = \gamma_0 + X_i \gamma_1 + \bar{X} \gamma_2 + \tilde{K} \gamma_3 + \gamma_4 \bar{Y}^* + \gamma_5 A_i + \gamma_6 \bar{A} + \epsilon_i - \gamma_4 \bar{\epsilon}. \quad (3.5)$$

Before turning to the interpretation of the exogenous peer effect, it is first useful to describe the properties of  $\gamma_4$ . For expositional purposes, I assume  $\alpha_7 \geq 0$  so that effort and peer effort are weakly complementary inputs to achievement production. This is consistent with the idea that harder working peers create a better learning environment. While the effort best response is increasing in peer effort given the assumption of a conformity effect ( $\beta_3 > 0$ ),  $\alpha_7 \geq 0$  ensures that the achievement best response is also increasing in average peer achievement, i.e.,  $\gamma_4 \geq 0$ . Furthermore, to ensure that the average peer achievement is positive, requires that  $\gamma_4 < 1$ , which holds if  $\beta_2 > \beta_3$  or the direct cost of effort exceeds the conformity effect. Note, as an aside, that this is enough to ensure that shared inputs  $\tilde{K}$  enter the semi-structural achievement production function with the same sign as their marginal product,  $\alpha_3$ .

Therefore, the interpretation of  $\gamma_2$  follows similarly to the ability case above. The larger the individual effect and endogenous effect, and the smaller the exogenous peer effect, the more likely that  $\gamma_2$  take the opposite sign of  $\gamma_1$ . However, note that while the exogenous effects parameter takes a similar form in both models, there is not reason to expect the magnitude of the bias away from capturing the direct effect of peer characteristics to be the same. In fact, if contemporaneous spillovers are larger than peer ability spillovers as might be expected, the estimates of a peer effort model are further away from capturing the true direct effect of peer characteristics. Table 1 provides some suggestive evidence in support of these observations from estimates in the literature. Most notably, as mentioned above, the

exogenous effect parameter appears more likely to take on the “counterintuitive” sign when the peer achievement effect is larger in magnitude.

### 3.3 Individual-specific utility parameters

In this simple example, the utility parameters are the same across individuals and because achievement also enters linearly into the utility function, the model predicts that all peer groups reach the same effort equilibrium. Moving to a more flexible form of utility permits the effort equilibrium to vary across peer groups that differ in composition and also provides a more explicit role for parents or other home inputs. It also suggests an alternative mechanism through which spillovers from peer characteristics could enter the semi-structural achievement production function, further illustrating the difficulties in interpreting the exogenous effects parameter.

Suppose the marginal utility from achievement is individual-specific, i.e.,

$$U_i = \beta_{1i}Y_i - \frac{\beta_2}{2}e_i^2 + \beta_3e_i\bar{e},$$

where  $\beta_{1i} = \beta_{10} + X_i\beta_{11} + \bar{X}\beta_{12}$ .<sup>13</sup> I assume that  $\beta_{10}$ ,  $\beta_{11}$  and  $\beta_2$  non-negative, so that the marginal utility of achievement is weakly increasing in  $X_i$ .

In this case equation (3.5) is modified such that  $\gamma_0 = \frac{\alpha_6^2\beta_{10}}{\beta_2}$ ,  $\gamma_1 = \alpha_1 + \frac{\alpha_6^2}{\beta_2}\beta_{11}$ , and  $\gamma_2 = \alpha_2(1 - \gamma_4) - \gamma_4\alpha_1 + \frac{\alpha_6^2}{\beta_2}\beta_{12}$ . Note that only the individual’s own utility parameters enter into the achievement best response function, i.e.,  $i$  is making a best response to any level of achievement (effort) of his peers. Because of this, if peer characteristics positively affect the marginal utility  $i$  derives from achievement relative to the cost of effort, then it is more likely that peer characteristics enter positively into the achievement best response function.

Complementarities between effort and characteristics are likely to enter the best response in other ways. For instance, complementarities between a student’s effort and his own or his peers’ characteristics in achievement production would produce similar results to the above case. Utility-maximizing effort would then be increasing in own or peer characteristics because the marginal product of effort is increasing in these inputs. Furthermore, the

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<sup>13</sup>In a model of endogenous reference group formation it seems likely that  $\beta_3$  might also be a function of peer characteristics, i.e., where individuals place more weight on the actions of peers more “like” themselves. While this has interesting implications, it is beyond the scope of the present paper.

above framework simplifies by assuming that utility is linear in achievement. An argument could be made that marginal utility is either increasing or decreasing in achievement. If marginal utility is increasing in achievement, then students with “better”  $X_i$  would want to exert relatively more effort, which would produce similar results to the above framework. Alternatively, if the marginal utility of achievement is diminishing, this would lead to the opposite effect.

## 4 What does this mean for identification?

Explicitly modeling the source of the endogenous effect has at least two important implications for identification. First, as emphasized in [Cooley \(2006\)](#), it provides insight into a way to address the reflection problem and to separately identify the endogenous from the exogenous effects parameter in the semi-structural production function (3.5). Second, it may reconcile mixed results in the literature regarding the sign and existence of exogenous effects. However, given unobserved correlated effects and simultaneity concerns, obtaining consistent estimates of the semi-structural parameters is not trivial, as first discussed by [Manski \(1993\)](#). Effectively, the insight of treating the endogenous effect as deriving through an unobservable, as described in the previous sections, adds yet another layer to [Manski \(1993\)](#)’s reflection problem. Thus, even if we are able to obtain consistent estimates of the semi-structural parameters, we cannot interpret them as the direct effect of exogenous peer characteristics.

The question naturally arises that given the difficulty in interpretation described above, whether the semi-structural parameters are of interest to begin with. First, note that estimates of the individual and endogenous effects provide insight into the magnitude of the divergence of the exogenous effects parameter from the direct effect. In [Section 5](#), I further describe how estimates of the semi-structural parameters can be applied to the question of optimal classroom groupings. Because selection into peer groups has received considerable attention elsewhere and is tangential to the present argument, I maintain the assumption of random assignment to peer groups.

I begin by writing down the semi-structural equation for peer achievement, equation (3.5), explicitly accounting for variation across peer groups (classrooms)  $g$  and school years  $t$ . Recall that  $\tilde{K}_{gt} \equiv (K_{gt}, \mu_{gt})$ , where both  $K_{gt}$  and  $\mu_{gt}$  are observable to the students,

but only  $K_{gt}$  is observable to the econometrician. Achievement can then be expressed as a function of peer achievement and other inputs, i.e.,

$$Y_{igt} = \gamma_0 + X_i\gamma_1 + \bar{X}_{gt}\gamma_2 + K_{gt}\gamma_3 + \gamma_4\bar{Y}_{gt} + \gamma_5A_i + \gamma_6\bar{A}_{gt} + \mu_{gt} + \xi_{igt}, \quad (4.1)$$

where  $\gamma_5A_i + \gamma_6\bar{A}_{gt} + \mu_{gt} + \xi_{igt}$  is unobserved to the econometrician and  $\xi_{igt} \equiv \epsilon_{igt} - \gamma_4\bar{\epsilon}_{gt}$ .

Solving for average peer achievement and substituting back into equation (4.1), we have the reduced form equation for peer achievement, i.e.,

$$Y_{igt} = \pi_0 + X_i\pi_1 + \bar{X}_{gt}\pi_2 + K_{gt}\pi_3 + \zeta_{igt}, \quad (4.2)$$

where

$$\begin{aligned} \pi_0 &= \frac{\gamma_0}{1 - \gamma_4}, \\ \pi_1 &= \gamma_1, \\ \pi_2 &= \frac{\gamma_2 + \gamma_1\gamma_4}{1 - \gamma_4} \\ \pi_3 &= \frac{\gamma_3}{1 - \gamma_4}, \\ \zeta_{igt} &= \gamma_5A_i + \frac{\gamma_4\gamma_5 + \gamma_6}{1 - \gamma_4}\bar{A}_{gt} + \frac{1}{1 - \gamma_4}\mu_{gt} + \epsilon_{igt}. \end{aligned}$$

As originally discussed by [Manski \(1993\)](#), existence of a social effect, defined as  $\gamma_2 \neq 0$  and/or  $\gamma_4 \neq 0$ , can be determined given it is possible to recover consistent estimates of  $\pi_2$ . Before continuing, I consider what exactly estimates of  $\pi_2$  capture in terms of the structural parameters of the model.

In the simplest version of the model, a student's choice of effort is only affected by his peers, i.e., neither his own or his peers' characteristics matter. Under this assumption (or under the assumption that only student ability matters), estimates of  $\pi_2$  in equation (4.2) would be equivalent to  $\alpha_2$  the direct effect of peer characteristics in equation (3.2). Intuitively, in this version of the model, the effect of racial composition derives only through the direct spillover to achievement production, the effect picked up by reduced form estimates. This contrasts with models that begin by assuming that peer achievement belongs in the production function. When peer achievement proxies for an unobserved peer effect, there is no indirect effect of peer characteristics deriving through peer achievement. Therefore, the

social effect is equivalent to the exogenous peer spillover as it is traditionally conceived in this context.

The result does not hold up under more plausible assumptions. For instance, simply moving to the slightly richer model where an individual's marginal utility from achievement is a function of individual and peer characteristics, as discussed in Section 3.3, produces the indirect spillover deriving through the peer effort channel. In terms of structural parameters,

$$\pi_2 = \alpha_2 + \frac{\alpha_6^2(\beta_{12} + \beta_{11}\gamma_4)}{\beta_2(1 - \gamma_4)}.$$

Thus, the reduced form recovers the social effect, which is equivalent to the direct effect in this case plus an additional term, which captures the effect of peer characteristics deriving through the effects on utility-maximizing effort choices and the social multiplier induced by having more peers exerting higher or lower effort.

Much of the literature focuses on the identification of the existence of a social effect, rather than distinguishing between endogenous and exogenous effects. For least-squares to obtain consistent estimates of  $\vec{\pi}$ , a necessary condition is that  $E(\zeta_{igt}|X_i, \bar{X}_{gt}, K_{gt}) = 0$ . This breaks down into the following conditions:

A1.  $E(A_i|X_i, \bar{X}_{gt}, K_{gt}) = 0,$

A2.  $E(\bar{A}_{gt}|X_i, \bar{X}_{gt}, K_{gt}) = 0,$

A3.  $E(\mu_{gt}|X_i, \bar{X}_{gt}, K_{gt}) = 0.$

Careful discussion of these conditions in the achievement context can be found elsewhere in the literature, such as in [Hanushek et al. \(2003\)](#) and [Moffitt \(2001\)](#). I briefly summarize some of the concerns and solutions below, though the focus in this paper is to highlight how the model helps inform identification of the endogenous effect parameter, which follows further below.

Under random assignment, the primary concern with (A1) and (A2) is that the observed characteristics and unobserved ability of a student are likely to be correlated. One way around this problem is to reinterpret the marginal effect of individual and peer characteristics as including ability. For instance, if policy makers are looking for ways of optimally assigning students to classrooms, it may be that differentiating between effects deriving through ability,

which they do not observe, and observable peer characteristics is not important. In other words, the question would simply be one of interpretation. For instance, we may find that having peers with better-educated parents raises achievement, but we remain agnostic about whether this relationship is picking up the fact that these peers are likely to be more “able” (through intergenerational human capital transfer-type stories) or whether the fact that the parents are better-educated in itself is helping in some way.

However, distinguishing between these channels may become important if schools assign students based on some measure of ability. For example, policy makers who seek to maintain racial balance in schools without explicitly resorting to race have turned to other observable factors, such as prior achievement and free/reduced price lunch status, with an eye toward not having too many “low-performers” or low-income students isolated in a single school. Thus, the alternative of using peer’s prior achievement to proxy for this unobserved ability may be most policy relevant, while at the same time further complicating the interpretation of exogenous effects. This introduces an additional complication, that  $\mu_{gt}$  cannot be correlated over time, i.e.,  $E(\mu_{gt}|\bar{Y}_{gt-1}, \cdot) = 0$ .

Another option would be to find some other variable that signals this unobserved component of ability. [Cooley \(2006\)](#) suggests one example for the context of reading achievement—portion of leisure time spent reading for fun. The intuition is simply that free reading time is positively correlated with reading ability, either because those who read more become more able readers or those who find reading easier tend to derive more utility out of it. The benefit of this type of proxy is that it may not be as directly related to achievement production, and less likely to induce bias through unobserved school inputs, though it is also less frequently observed and potentially less directly applicable to policy settings. Yet, in a setting where teachers know more about ability than is revealed in test scores, it is difficult to say which is more relevant.

One other solution is to interpret contemporaneous peer achievement as proxying for an aggregate of peer ability and peer effort spillovers under some fairly strict functional form assumptions. For instance, one way that peer achievement would serve as a sufficient statistic to capture both types of spillovers is if (1) the marginal product of own ability equals the marginal product of effort, (2) the marginal product of peer effort equals the marginal product of peer ability, and (3)  $\beta_3 = 0$ , so that an effect of peer effort derives solely through achievement production spillovers.

The arguments for controlling for individual ability are similar. The literature often estimates value-added production functions. Lagged achievement potentially controls for prior inputs to achievement, which may not be included in  $X_{igt}$  because of data limitations, as well as unobserved ability. In this specification, often twice-lagged peer achievement is used to proxy for peer ability, otherwise the two exogenous characteristics  $Y_{igt-1}, \bar{Y}_{gt-1}$  are likely to be correlated through unobserved shared inputs. It is difficult to develop a theoretical model that rationalizes the combined use of lagged achievement to control for ability and twice-lagged peer achievement to control for peer ability. An alternative pursued, often in combination with a value-added specification, is to include a student fixed effect. While these different approaches have some relative merit, it does seem useful to have some symmetry between the treatment of unobserved individual and peer characteristics. This symmetry cannot be achieved by using a value-added specification combined with twice-lagged peer achievement, unless ability can reasonably be treated as a fixed effect, i.e., no human capital accumulation.

To obtain consistent estimates of  $\pi_2$ , A3 is also a concern. Under random assignment, this requires that resource inputs do not change systematically with peer characteristics. If  $\mu_{gt}$  captures teacher quality, this suggests that teachers do not vary inputs according to the characteristics of their class. On the one hand, this assumption seems unreasonable because it severely limits the role of teachers. On the other, due to considerable costs of developing new lesson plans, there may be considerable stickiness in the teacher's inputs so that the teacher does not respond to relatively minor variations in class characteristics from year to year. If we consider the possibility that a teacher using a particular teaching technique becomes more effective with a given set of students with characteristics  $\bar{X}$ , this can be interpreted as a type of peer effect, namely an agglomeration effect.

Because the above arguments regarding the interpretation of exogenous effects center around the existence of peer effort spillovers, I now turn to the question of separately identifying  $\gamma_2$  and  $\gamma_4$ . It is easily shown that the endogenous and exogenous peer spillovers are not separately identified from the reduced form parameters. Namely, let  $\dim(X_{igt}) = \dim(\bar{X}_{gt}) = d_1$  and  $\dim(K_{gt}) = d_2$ . Then, the number of parameters in equation (4.1),  $2d_1 + d_2 + 2$ , exceeds the number of reduced form parameters,  $2d_1 + d_2 + 1$ .

This result points to the considerable difficulty introduced by using contemporaneous peer achievement to proxy for unobserved peer effort. However, the effort model suggests a potential exclusion restriction that can help identify  $\gamma_4$ . Note that peer utility parameters

do not affect  $i$ 's achievement directly. Thus, if we can identify individual characteristics ( $Z_{it}$ ) that affect the utility derived from achievement (or disutility from effort), but do not affect achievement directly; these may offer a means of identifying the best response function. To elaborate, let  $\beta_{1i} = \beta_{10} + X_i\beta_{11} + \bar{X}\beta_{12} + Z_{it}\beta_{13}$ . Equation (4.1) becomes

$$Y_{igt} = \gamma_0 + X_i\gamma_1 + \bar{X}_{gt}\gamma_2 + K_{gt}\gamma_3 + \gamma_4\bar{Y}_{gt} + \gamma_7Z_{it} + \gamma_5A_i + \gamma_6\bar{A}_{gt} + \mu_{gt} + \xi_{igt}, \quad (4.3)$$

where  $\gamma_7 \equiv \frac{\alpha_6^2\beta_{13}}{\beta_2}$ .

The reduced form equation is then

$$Y_{igt} = \pi_0 + X_i\pi_1 + \bar{X}_{gt}\pi_2 + \tilde{K}\pi_3 + Z_{it}\pi_4 + \bar{Z}_{gt}\pi_5 + \tilde{\xi}_{igt}.$$

Given that  $\dim(Z_{it}) \geq 1$ , we have that there are at least as many reduced form as semi-structural parameter, i.e.,  $1 + 2d_1 + d_2 + 2d_3 \geq 2 + 2d_1 + d_3$ . Effectively, the average peer utility-shifter  $\bar{Z}_{gt}$  provides a potential exclusion restriction. However, it must also be independent of unobservables, most notably the unobserved group effect  $\mu_{gt}$ .

A particularly useful type of exclusion restriction would be a policy that affects the incentives of some students in the peer group but not others. Cooley (2006) offers one example—the introduction of student accountability standards, which threaten students with retention if they do not perform above a certain level. Relying on the idea that only “low-achievers” suffer the threat of this policy, the instrument is then the percentage of peers held accountable. Another potential exclusion restriction is a family-level characteristic that affects choice of effort. For this to work, however, it cannot affect achievement directly. One example might be the presence of a high-achieving sibling.

## 4.1 Ability Model

Now, I briefly contrast the implications for identification in the ability model. The semi-structural equation (3.3) in this case can be written as

$$Y_{igt} = \tilde{\gamma}_0 + X_i\tilde{\gamma}_1 + \bar{X}_{gt}\tilde{\gamma}_2 + K_{gt}\tilde{\gamma}_3 + \tilde{\gamma}_4\bar{Y}_{gt} + \tilde{\gamma}_5A_i + \tilde{\gamma}_6e_{igt} + \tilde{\gamma}_7\bar{e}_{gt} + \mu_{gt} + \tilde{\xi}_{igt},$$

where  $\tilde{\eta}_{igt} \equiv \tilde{\gamma}_5A_i + \tilde{\gamma}_6e_{igt} + \tilde{\gamma}_7\bar{e}_{gt} + \mu_{gt} + \tilde{\xi}_{igt}$  and  $\tilde{\xi}_{igt} \equiv \epsilon_{igt} - \tilde{\gamma}_4\bar{\epsilon}_{gt}$ .

Note that in contrast to the above, we can eliminate the apparent simultaneity problem by substituting lagged peer achievement into the achievement production function, i.e.,

$$Y_{igt} = \tilde{\gamma}_0 + X_i \tilde{\gamma}_1 + \bar{X}_{gt} \tilde{\gamma}_2 + K_{gt} \tilde{\gamma}_3 + \tilde{\gamma}_4 \bar{Y}_{gt-1} + \tilde{\gamma}_5 A_i + \tilde{\gamma}_6 e_{igt} + \tilde{\gamma}_7 \bar{e}_{gt} + \mu_{gt} + \tilde{\xi}_{igt}, \quad (4.4)$$

and we can thus treat peer achievement as a predetermined variable. Then under the assumption that  $E(\tilde{\eta}_{igt}|X_i, \bar{X}_{gt}, \bar{Y}_{gt-1}, K_{gt}) = 0$ , the parameters  $\vec{\gamma}$  are identified. This can then be treated equivalently to identifying the parameters of the reduced form equation (4.2) above. However, in contrast to Assumptions A1 to A3, we need the following conditions:

$$A1'. E(A_i|X_i, \bar{X}_{gt}, K_{gt}, \bar{Y}_{gt-1}) = 0,$$

$$A2'. E(e_{igt}|X_i, \bar{X}_{gt}, K_{gt}, \bar{Y}_{gt-1}) = 0,$$

$$A3'. E(\bar{e}_{gt}|X_i, \bar{X}_{gt}, K_{gt}, \bar{Y}_{gt-1}) = 0 \text{ or } \tilde{\gamma}_7 = 0,$$

$$A4'. E(\mu_{gt}|X_i, \bar{X}_{gt}, K_{gt}, \bar{Y}_{gt-1}) = 0.$$

The assumption regarding individual ability A1' is similar to above, however the remaining assumptions merit further discussion. Assumption A2' is satisfied if effort is randomly distributed across students. For instance, better-educated parents do not have children who work harder in school on average. Furthermore, it must be independent of observed classroom inputs,  $K$ , such as teacher experience, and cannot be affected by the “ability” or observable characteristics of the peers. The restrictiveness of these assumptions was discussed in Section 2.

A3' requires that either peer effort does not affect achievement production or that average peer effort is mean independent of all the inputs into achievement production, which imposes a similar constraint to A2'. Most notably, conditioning on prior peer achievement suggests that peer effort cannot be correlated over time.

Finally, A4' is similar to A3 in the effort case, with the additional complication introduced by the lagged model that the unobserved productivity  $\mu_{gt}$  must be mean independent of average peer achievement in the previous period. This imposes the restriction that the unobserved productivity of the student's classroom, such as teacher quality, cannot be correlated over time. This may hold if students are randomly assigned to classrooms every year or, after conditioning on school fixed effects, if they are randomly assigned to teachers within schools each year.

In light of the implausibility of Assumptions A3' and A4', it is worth considering whether an exclusion restriction could exist, analogously to the peer effort model, which would shift peer achievement (or its lagged value) independently of the unobserved components. However, because ability is a characteristic of the student and effort is assumed to be exogenous, no analogue exists in the ability case. In fact, even if we moved to a model with endogenous effort choice but maintained the assumption that only peer ability (not effort) spillovers mattered, there would be no exclusion restriction.

An alternative way to think about the problem is to interpret  $\bar{Y}_{gt-2}$  as a peer characteristic, i.e., an element of  $\bar{X}_{gt}$ , and equation (4.4) as the reduced form of the achievement best response described in equation (4.1). Then, only A1' and A4' need hold in order to obtain consistent estimates of the reduced form parameters. Intuitively, this follows because we are not trying to distinguish between causal channels, but rather correlational evidence is sufficient. If on average students perform better in classrooms where peers have better-educated parents, we estimate the total social effect of these peers. However, note that while this works in the linear-in-means case, it will not hold more generally. For instance, suppose that lower-achievers receive higher spillovers from average peer effort than higher-achievers. Then, attempting to estimate some sort of reduced form equation of the form above would not capture the idea that average achievement is higher in mixed than in stratified classes. I return to this below.

## 5 So what? Optimal Grouping Implications

In the previous sections, I develop intuition for why contemporaneous peer achievement spillovers matter and the resulting implications for identification, ultimately motivating the importance of the reflection problem for deriving causal estimates in the achievement context. In doing so, I attempt to draw a sharp distinction between the unobserved peer ability and peer effort spillover frameworks. One well-known distinction between the exogenous spillovers implied by the ability model and the endogenous spillovers of the effort model is that only the latter generates social multiplier effects, as originally discussed by Manski (1993) and emphasized by Glaeser et al. (2003), Graham (2004), among others. Given that such social multipliers exist, the implications for policy can be quite different. To illustrate, consider the No Child Left Behind Act, which encourages schools to shift emphasis toward traditionally disadvantaged students, and therefore also potentially away from traditionally

advantaged students. If endogenous effects are present, the improvements in the achievement of disadvantaged students will spillover to advantaged students. Furthermore, the gains from the increased resources to disadvantaged students will also be multiplied through peer spillover effects. Therefore, failure to take into account the social multiplier effects could severely misstate the effect of these types of policies.

Yet, as discussed in the introduction, another argument for ignoring the reflection problem is that reduced form estimates are often sufficient for policy. One context where this might apply is for optimal grouping-type questions, which investigate the *ceteris paribus* effect of altering peer group composition on achievement. Often the questions of interest center on observable characteristics. Does tracking students by prior achievement improve performance? If increased school choice leads to exit of the children with better-educated or higher-income parents, does this hurt the students left behind? Does racial integration improve the performance of black students? Given that peer groups are altered based on observable measures, this begs the question whether the distinction between ability and effort spillovers matters in practice. In other words, the reduced form estimates precisely the relationship of interest, the correlation of observable peer characteristics with outcomes. The reason *why* these characteristics matter may then be of secondary importance for answering the types of optimal grouping questions described above. In this section, I explore the extent to which this is the case.

Because the literature on racial composition effects is extensive and of continued concern to policy makers, I center the discussion in this context. I maintain the assumption that consistent estimates of the reduced form parameters are available, i.e., the  $\pi$ 's in equation (4.2) or the  $\tilde{\gamma}$ 's in equation (4.4), when it is interpreted as the reduced form of equation (4.1). To be clear, by *consistent* I mean that the parameters are capturing peer effects rather than some unobserved correlated effect. In equation (4.2), peer racial composition could be proxying for a whole host of characteristics such as ability, income, or effort, and should be interpreted accordingly.

## 5.1 Linear-in-Means Model.

**Reduced Form Estimates** Given the difficulties inherent in separating effort or ability spillovers from contextual peer effects, it is useful to begin by considering whether reduced-form estimates of the relationship between observable peer composition measures (other than

lagged peer achievement) and achievement, as described by equation (4.2), are sufficient for determining optimal groupings in the linear-in-means model.

While  $\pi_2$  describes the effect of marginal changes in peer composition, to really understand the implications of larger scale reallocation requires taking into account that by necessity a decrease in the percentage black in one classroom means an increase in another (assuming class size constraints and fixed student population). The larger policy question might then be how moving from a completely segregated setting to an integrated setting affects achievement. A well-known property of the linear-in-means model is that average achievement is not changed by altering peer composition—the gains to one group from any reallocation are perfectly offset by the losses to another. However, reallocation under the linear-in-means model does have equity implications, affecting the average achievement of subgroups. Most particularly, it is the racial achievement gap, rather than the overall average, that is central to recent federal initiatives, namely the No Child Left Behind Act. Therefore, I take the average achievement of white and black students as the outcomes of interest.

Note that in the reallocation context, by necessity students are not only reassigned to peers but also to teachers. The ideal experiment to isolate the effect of regrouping might be to fix teacher quality at some value, say  $\bar{\mu}$ , for all classrooms and then ask the effect of reassigning students to peers. This would allow us to isolate the racial composition effect from the unobserved correlated effects. Under the assumption of random assignment of students to classrooms (and hence teacher quality), the reduced form estimates can be applied to predict the effect of moving from the extreme of a perfectly segregated setting to an integrated setting on the average achievement of black and white students. This follows because of the common parameters assumption and random assignment, which effectively acts in expectation as if teacher quality were fixed.

However, random assignment is not the norm, and often researchers attempt to recover racial composition effects in a context where there is sorting of students and teachers to peer groups. The fundamental problem in deducing racial composition effects is that generally schools with higher concentrations of black students are also those that are worse in unobservable ways, violating the assumption that  $E(\mu_{gt}|\bar{X}_{gt}) = 0$ . Teacher quality in particular is notoriously difficult to measure, though both empirical and anecdotal evidence suggest that

it matters.<sup>14</sup> For instance, [Clotfelter et al. \(2006\)](#) find evidence that more highly qualified teachers tend to be matched with more affluent schools or schools with fewer minority students. The literature recognizes this problem. One method used to separately identify racial composition effects from unobserved correlated effects is to exploit some type of within-school variation.<sup>15</sup> Evidence in [Clotfelter et al. \(2006\)](#) suggesting that most teacher-student matching occurs between schools supports the use of school fixed effects to correct for this type of selection.

Under the assumption that teachers are matched to students, with predominantly white schools having relatively higher teacher quality on average than predominantly black schools, the reduced form results cannot be used to extrapolate effects of larger scale policy changes, such as integrating schools within a district. The intuition is simple. Suppose we fix teacher quality at some value  $\bar{\mu}$ , which is the average teacher quality in the district. In the perfectly integrated system, black students would receive higher teacher quality on average and white students lower. Without estimates of the social multiplier effect, it would not be possible to separate an effect of racial integration from a teacher effect. This is an example where estimates of the semi-structural parameters, equation (4.1) would be necessary for determining the larger scale effect of desegregation.

Note that in the above experiment, because teacher quality has the same effect on white and black students, average achievement for the student population overall does not change. Given the restrictiveness of these assumptions and evidence of heterogeneous responses to peers, I briefly describe implications of a more general framework below. But, first I consider another rationale for estimating the semi-structural equation, i.e., racial composition effects conditional on achievement. In particular, I focus on estimates of equation (4.4).

**Conditioning on Achievement** Recently, the Supreme Court ruled that it is not constitutional in many circumstances to use race as a basis for assigning students to school. The concern is that this will undo much of the progress made toward integration over the years since *Brown v. Board of Education*, which may in turn have negative consequences to students. In fact, many districts have witnessed an increase in segregation over the past decade as they have been released from the obligation of proactively integration.<sup>16</sup> A number of

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<sup>14</sup>See [Hoxby \(2006\)](#).

<sup>15</sup>For instance, see [Hoxby \(2000\)](#), [Ammernueller and Pischke \(2006\)](#), [Vigdor and Nechyba \(forthcoming\)](#) and [Hanushek et al. \(2004\)](#).

<sup>16</sup>See [Clotfelter et al. \(2005\)](#) for a discussion

districts have attempted to maintain some degree of racial integration by assigning students based on other observables, such as free/reduced price lunch status and prior achievement. A question of interest is then whether these race-blind integration policies can substitute for racial integration in terms of achievement effects.

In comparison to historical studies that estimate desegregation effects from comparisons of outcomes before and after integration, one benefit of peer effects in achievement style studies is to address precisely this sort of question, by contrasting peer groups of various achievement, racial and income composition and isolating the relative importance of these different channels of influence. Therefore, the relationship of interest is the effect of racial composition conditional on lagged peer achievement, as in equation (4.4).<sup>17</sup> Recall that the interpretation of the exogenous effect parameter,  $\tilde{\gamma}_2$ , is complicated by the fact that it is picking up the direct effect less the indirect effect deriving through peer ability, as discussed in Section 3.<sup>18</sup>

Yet, from the discussion so far it is unclear whether  $\alpha_2$  or  $\tilde{\gamma}_2$  is more relevant for policy purposes. Given that the linear-in-means model is correct and assignment is being made on the lagged values of the observable standardized achievement measures, the coefficient on racial composition in equation (4.4) can be correctly interpreted as describing whether racial composition matters after controlling for average peer achievement. However, this is not true if policy makers integrate based on some ability that is unobserved to the econometrician, i.e., IQ scores, classroom performance, or parental assertiveness. While standardized achievement scores may be a valid proxy for ability, the coefficient on percentage nonwhite cannot be interpreted as whether or not racial composition matters conditional on ability. The distinction is subtle, but could nonetheless be important for deriving policy implications.

Given that the  $\tilde{\gamma}_2$  is interpreted as a reduced form of the effort model, equation (4.1), a similar argument as above follows for applying the reduced-form parameters to estimating the average achievement of white and black students. Local estimates using within-school variation cannot be used to extrapolate larger scale effects of desegregation in the context

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<sup>17</sup>Note that in the case where equation (4.4) is interpreted as the reduced form version of the effort model, the relation of  $\tilde{\gamma}_2$  to the structural parameters is still as described in equation (3.3), i.e., the social effect is picking up the direct spillover less the indirect spillover deriving through the peer achievement proxy for ability. Again, this result follows because characteristics do not enter effort choices.

<sup>18</sup>Note that in the simplest setting where effort is not a function of own or peer characteristics, the direct effect can be recovered from the estimates of  $\tilde{\gamma}$ , the semi-structural parameters, i.e.,  $\alpha_2 = (\tilde{\gamma}_2 + \tilde{\gamma}_4 \tilde{\gamma}_1) / (1 - \tilde{\gamma}_4)$ . Note, however, that when individual or peer characteristics help determine utility-maximizing effort, this result no longer holds.

of teacher sorting.

## 5.2 Allowing for Nonlinearities

Both theory and empirical evidence suggest that the linear-in-means model may not provide a good approximation of peer effects in practice. In particular, evidence suggests that blacks and whites may respond differently to peers, with important implications for the usefulness of desegregation policies to narrow the racial achievement gap.<sup>19</sup> For instance, [Hanushek et al. \(2004\)](#) find that the percentage of black peers has a stronger negative effect on black students than on whites. [Echenique and Fryer \(2006\)](#) find that the degree of segregation within schools, measured by the cross-racial social interactions, for black students is highly nonlinear and increases with the percentage black of the school.

In determining the potential costs of academic tracking, it is often assumed that low-achievers benefit relatively more from being grouped with higher-achieving peers than high achievers. In this context, mixed-ability classes provide the highest average achievement. Extending to the question of desegregation, given that black students are more highly concentrated in the lower tails of the achievement distribution, integration could also raise average achievement. The literature generally supports the existence of these types of nonlinearities.<sup>20</sup> Thus, as [Hoxby \(2000\)](#) discusses, moving beyond linear-in-means models of peer effects is likely to be critical for developing interesting policy implications.

Even in the simplest case where we allow the marginal effect of peer characteristics and peer achievement in equation (4.1) to vary across races, the semi-structural equation no longer reduces to a neat reduced form relationship between average peer characteristics and average peer achievement. Separating out endogenous from exogenous peer effects is then likely to be critical for determining the effects of the reallocation of students to classrooms. This is only further complicated if responses to teachers vary across students, as evidence suggests.<sup>21</sup> Therefore, addressing the reflection problem is only likely to become more relevant in the context of heterogeneous peer effects.

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<sup>19</sup>For instance, see [Cooley \(2006\)](#), [Hanushek et al. \(2004\)](#), [Hoxby and Weingarth \(2005\)](#), [Fryer and Torelli \(2005\)](#), among others.

<sup>20</sup>See, for instance, [Cooley \(2006\)](#), [Ding and Lehrer \(2006\)](#), [Hanushek et al. \(2003\)](#), [Hoxby and Weingarth \(2005\)](#) for evidence of nonlinearities. [Ammermueller and Pischke \(2006\)](#) is an exception.

<sup>21</sup>For instance, [Dee \(2005\)](#) finds evidence that same gender teachers can improve student achievement.

## 6 Conclusion

In this paper, I attempt to clarify the rationale for endogenous peer effects, i.e., the inclusion of peer achievement in the achievement production function. I take as an underlying premise that peer achievement per se does not matter in achievement production, but rather serves as a proxy for an unobserved quality of the peer group, as generally argued in the literature. I contrast two types of peer spillovers that peer achievement could capture—unobserved effort and ability. The important distinction is that only the former is truly endogenous, the latter being predetermined. The contrast is of practical importance because it suggests that using lagged measures of peer achievement, an approach generally taken in the literature, fails to capture important behavioral spillovers of peers.

In the paper I highlight three areas where the literature on peer effects in educational achievement may be misguided. The first is the tendency to ignore the reflection problem, minimizing the importance of simultaneity concerns for identification of peer spillovers. Lagged measures of peer achievement are generally preferred because they are less likely to be correlated with unobserved group effects, such as teacher quality, whereas the simultaneity concerns associated with including contemporaneous peer achievement are thought to be insoluble. I argue rather that theory suggests natural exclusion restrictions that permit the identification of endogenous peer effects, that are not apparent in the ability-based framework that is commonly assumed.

The second is that more careful consideration should be given to the interpretation of estimates of the spillovers from peer characteristics. Using peer achievement to proxy for unobserved peer “quality” suggests that peer characteristics may appear to be correlated with achievement even if they do not directly affect achievement, but only indirectly as a proxy for peer quality. Furthermore the indirect proxy channel works in opposition to the direct externality that is commonly assumed, suggesting that the intuition that a student should be positively affected by peers with characteristics conducive to achievement may not always bear out in estimates.

Third, I show that reduced form estimates of the social effect of peers are generally not sufficient for determining the effects of regrouping students on the achievement of different subgroups, even assuming a linear-in-means framework with homogeneous treatment effects. Therefore, determining the causal effect of peers, i.e., separating endogenous from exogenous

peer effects, is central to developing viable policy implications of large scale reallocations of students.

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Table 1: Recent Studies on Peer Achievement and Composition.

Studies	Context	Source /Specification	Peer Achievement	Sign /Magnitude	Peer Characteristics	Sign /Magnitude
Hanushek et al. (2003)	Public Schools Texas, US	Table 2, Column 3 Student Fixed Effects	Average Math Score T-2	0.15	Proportion Eligible for Reduced Price Lunch	0.1
Vigdor and Nechyba (2004)	Public Schools N. Carolina, US	Table 2, Columns 3 and 6, No Student Fixed Effects	Average Math Score T-2	0.0741	% Black in Classroom	-0.1327
Betts and Zau (2004)	Public Schools, San Diego, US	Table 3, Column 1, Student Fixed Effects	Average Math Score T-1	1.9295	% Black at School Level	Not Reported
Hanushek et al. (2004)	Public Schools Texas, US	Table 1, Column 7 Student Fixed Effects	Average Math Score T-2	0.01	% Black in Grade	-0.25
Henry and Rickman (2007)	Preschool Georgia, US	Table 4, Column 1	Cognitive Skills (WJ-AP)	0.39	% Black in Classroom	0.12
Gibbons and Telhaj (2005)	Public Schools, England	Table 5, Column 5	Average Math Score T-3	0.218	% White in School-Grade	-0.004
Cooley (2006)	Public Schools, N. Carolina	Table 3, Col. 4	Average Reading Score T	.48	% nonwhite in classroom	.10