Complementarity and Aggregate Implications of Assortative Matching: A Nonparametric Analysis*

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First Draft: July 2004
This version: May 2006

Abstract

This paper presents methods for evaluating the effects of reallocating an indivisible input across production units. When production technology is nonseparable such reallocations, although leaving the marginal distribution of the reallocated input unchanged by construction, may nonetheless alter average output. Examples include reallocations of teachers across classrooms composed of students of varying mean ability and altering assignment mechanisms for college roommates in the presence of social interactions. We focus on the effects of reallocating one input while holding the assignment of another, potentially complementary input, fixed. We present a class of such reallocations – correlated matching rules – that includes the status quo allocation, a random allocation, and both the perfect positive and negative assortative matching allocations as special cases. Our econometric approach involves first nonparametrically estimating the production function and then averaging this function over the distribution of inputs induced by the new assignment rule. Formally our methods build upon the partial mean literature (e.g., Newey 1994, Linton and Nielsen 1995). We derive the large sample properties of our proposed estimators and assess their small sample properties via a limited set of Monte Carlo experiments. An application, assessing the effects of spousal sorting on child education (e.g., Kremer 1996), concretely illustrates our methods.

JEL Classification: C14, C21, C52

Keywords: *Average Treatment Effects, Complementarity, Aggregate Redistributional Effects*

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*Financial support for this research was generously provided through NSF grant SES 0136789 and SES 0452590. We thank participants in the Harvard-MIT and Brown Econometrics Seminars for comments. We thank Cristine Pinto for excellent research assistance.

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1 Introduction

Consider an input into a production process. For each firm output may be monotone in this input, but at different rates. If the input is indivisible and its aggregate stock fixed, it will be impossible to simultaneously raise the input level for all firms. In such cases it may be of interest to consider the output effects of *reallocations* of the input across firms. Here we investigate econometric methods for assessing the effect on average output of such reallocations. A key feature of reallocations is that while potentially altering input levels for each firm, they keep the marginal distribution of the input across the population of firms fixed.

We consider a two parameter family of feasible reallocations that include several focal allocations as special cases. Reallocations in this family may depend on the distribution of a second input or firm characteristic. This characteristic may be correlated with the firm-specific return to the input to be reallocated.

One reallocation redistributes the input across firms such that it has perfect rank correlation with the second input. We call this allocation the positive assortative matching allocation. We also consider a negative assortative matching allocation where the input is redistributed to have perfect negative rank correlation with the second input. A third allocation involves randomly assigning the input across firms. This allocation, by construction, ensures independence of the two inputs. A fourth allocation simply maintains the status quo assignment of the input.

Our family of reallocations, which we call correlated matching rules, includes each of the above allocations as special cases. In particular the family traces a path from the positive to negative assortative matching allocations. Each reallocation along this path keeps the marginal distribution of the two inputs fixed, but is associated with a different level of correlation between the two inputs. Each of the reallocations we consider are members of a general class of reallocation rules that keep the marginal distributions of the two inputs fixed.

We derive an estimator for average output under correlated matching. Our estimator requires that the first input is exogenous conditional on the second input and additional firm characteristics. Except for the case of perfect negative and positive rank correlation the estimator has the usual parametric convergence rate. For the two extremes the rate of convergence is slower. In all cases we drive the asymptotic distribution of the estimator.

Our focus on reallocation rules that keep the marginal distribution of the inputs fixed is appropriate in applications where the input is indivisible, such as in the allocation of teachers to classes or managers to production units. In other settings it may be more appropriate to consider allocation rules that leave the total amount of the input constant by fixing its average level. Such rules would require some modification of the methods considered in this paper.

Our methods may be useful in a variety of settings. One class of examples concerns complementarity of inputs in production functions (e.g. Athey and Stern, 1998). If the first and second inputs are everywhere complements, then the difference in average output between the positive and negative assortative matching allocations provides a nonparametric measure of the degree of complementarity. This measure is invariant to monotone transformations of the inputs. If the production function is not supermodular interpretation of this difference is not straightforward, although it still might be viewed as some sort of 'global' measure of input complementarity. With this concern in mind we also provide a local measure of complementarity. In particular we consider whether small steps away from the status quo and toward the perfect assortative matching allocation raise average output.

A second example concerns educational production functions. Card and Krueger (1992) study the relation between educational output as measured by test scores and teacher quality. Teacher quality may improve test scores for all students, but average test scores may be higher or lower depending on whether, given a fixed supply of teachers, the best teachers are assigned to the least prepared students or vice versa. Parents concerned solely with outcomes for their own children may be most interested in the effect of raising teacher quality on expected scores. A school board, however, may be more interested in maximizing expected test scores given a fixed set of classes and teachers by optimally matching teachers to classes.

A third class of examples arises in settings with social interaction (c.f., Manski 1993; Brock and Durlauf 2001). Sacerdote (2001) studies the peer effects in college by looking at the relation between outcomes and roommate characteristics. From the perspective of the individual student or her parents it may again be of interest whether a roommate with different characteristics would, in expectation, lead to a different outcome. This is what Manski (1993) calls an exogenous or contextual effect. The college, however, may be interested in a different effect, namely the effect on average outcomes of changing the procedures for assigning roommates. While it may be very difficult for a college to change the distribution of characteristics in the incoming classes, it may be possible to change the way roommates are assigned. In Graham, Imbens and Ridder (2006b) we consider average effect of segregation policies.

In all these cases we focus on policies that change the way a fixed distribution of inputs is allocated to a population of units with a fixed distribution of characteristics. We are interested in the effect such policies have on the distribution of outcomes. Typically the most interesting measure will be the average level of the outcome. We will call the causal effects of such policies Aggregate Redistributional Effects (AREs).

If production functions are additive in inputs the questions posed above have simple answers: average outcomes are invariant to input reallocations. While reallocations may raise individual outcomes for some units, they will necessarily lower them by an offsetting amount for others. Reallocations are zero-sum games. With additive and linear functions even more general assignment rules that allow the marginal input distribution to change while keeping its average level unchanged do not affect average outcomes. In order for these questions to have interesting answers, one therefore needs to explicitly recognize and allow for non-additivity and non-linearity of a production function in its inputs. For this reason our approach is fully nonparametric.

The current paper builds on the larger treatment effect and program evaluation literature.[1] More directly, it is complementary to the small literature on the effect of treatment assignment rules (Manski, 2004; Dehejia, 2004; Hirano and Porter, 2005). Our focus is different from that in the Manski, Dehejia, and Hirano-Porter papers. First, we allow for continuous rather than discrete or binary treatments. Second, our assignment policies to do not change the marginal distribution of the treatment, whereas in the previous papers treatment assignment for one unit is not restricted by assignment for other units. Our policies are fundamentally redistributions. In the current paper we focus on estimation and inference for specific assignment rules. It is also interesting to consider optimal rules as in Manski, Dehejia and Hirano-Porter. The class of feasible reallocations/redistributions includes all joint distributions of the two inputs with fixed marginal distributions. When the inputs are continuously-valued, as we assume in the current paper, the class potential rules is very large. Characterizing the optimal allocation within this class is therefore a non-trivial problem. When both inputs are discrete-valued the problem with finding the optimal allocation is tractable as the joint distribution of the

[1] For recent surveys see Angrist and Krueger (2001), Heckman, Lalonde and Smith (2001), and Imbens (2004).

inputs is characterized by a finite number of parameters. In Graham, Imbens and Ridder (2006a) we consider optimal allocation rules when both inputs are binary, allowing for general complementarity or substitutability of the inputs.

Our paper is also related to recent work on identification and estimation of models of social interactions (e.g., Manski 1993, Brock and Durlauf 2001). We do not focus on directly characterizing the within-group structure of social interactions, an important theme of this literature. Rather our goal is simply to estimate the average relationship between group composition and outcomes. The average we estimate may reflect endogenous behavioral responses by agents to changes in group composition, or even equal an average over multiple equilibria. Viewed in this light our approach is reduced form in nature. However it is sufficient for, say, an university administrator to characterize the outcome effects of alternative roommate assignment procedures.

The econometric approach taken here builds on the partial mean literature (e.g., Newey, 1994; Linton and Nielsen, 1995). In this literature one first estimates a regression function nonparametrically. In the second stage the regression function is averaged, possibly after some weighting with a known or estimable weight function, over some of the regressors. Similarly here we first estimate a nonparametric regression function of the outcome on the input and other characteristics. In the second stage the averaging is over the distribution of the regressors induced by the new assignment rule. This typically involves the original marginal distribution of some of the regressors, but a different conditional distribution for others. Complications arise because this conditional covariate distribution may be degenerate, which will affect the rate of convergence for the estimator. In addition the conditional covariate distribution itself may require nonparametric estimation through its dependence on the assignment rule. For the policies we consider the assignment rule will involve distribution functions and their inverses similar to the way these enter in the changes-in-changes model of Athey and Imbens (2005).

The next section lays out our basic model and approach to identification. Section 3 then defines and motivates the estimands we seek to estimate. Section 4 presents of our estimators, and derives their large-sample properties, for the case where inputs are continuously-valued. Section **??** presents a simple test for the efficiency of the status quo allocation of inputs. Section **??** deals with estimation and inference in the case where inputs take on discrete values. In this case the problem is fully parametric and large sample standard errors can be computed using the delta method Section 5 presents an application and the results of a small Monte Carlo exercise.

2 Model

In this section we present the basic model and identifying assumptions. For clarity of exposition we use the production function terminology; although our methods are appropriate for a wide range of applications as emphasized in the introduction. Let $Y_i(w)$ be the output associated with input level w for firm $i = 1, \ldots, N$. We are interested in reallocating the input W across firms. We focus upon reallocations which hold the marginal distribution of W fixed. As such they are appropriate for settings where W is a plausibly indivisible input, such as a manager or teacher with a certain level of experience and expertise. The presumption is also that the aggregate stock of W is difficult to augment.

In addition to W there are two other (observed) firm characteristics that may affect output: X and Z, where X is a scalar and Z is a vector of dimension K. The first characteristic

X could be a measure of, say, the quality of the long-run capital stock, with Z being other characteristics of the firm such as location and age. These characteristics may themselves be inputs that can be varied, but this is not necessary for the arguments that follow. In particular the unconfoundedness or exogeneity assumption that we make for the first input need not hold for these characteristics.

We observe for each firm $i = 1, \ldots, N$ the level of the input, W_i, the characteristics X_i and Z_i, and the realized output level, $Y_i = Y_i(W_i)$. In the educational example the unit of observation would be a classroom. The variable input W would be teacher quality, and X would be a measure of quality of the class, e.g., average test scores in prior years. The second characteristic Z could include other measures of the class, e.g., its age or gender composition, as elements. In the roommate example the unit would be the individual, with W the quality of the roommate (measured by, for example, a high school test score), and the characteristic X would be own quality. The second set of characteristics Z could be other characteristics of the dorm or of either of the two roommates such as smoking habits (which may be used by university administrators in the assignment of roommates).

Our identifying assumption is that conditional on firm characteristics $(X, Z')'$ the assignment of W, the level of the input to be reallocated, is unconfounded or exogenous.

Assumption 2.1 (Unconfoundedness/Exogeneity)

$$Y(w) \perp W \,\Big|\, X, Z, \quad \textit{for all } w \in \mathcal{W} \subset \Re^1.$$

This type of assumption is common in the (binary) treatment effect literature where its precise form is due to Rosenbaum and Rubin (1983). To interpret the assumption, consider first the case where there are no additional characteristics (i.e., no $\dim(X) = \dim(Z) = 0$). Then Assumption 2.1 requires that $Y(w) \perp W$. This implies that the average output we would observe if all firms were assigned input level $W = w$ equals the average output among firms that were in fact assigned input level $W = w$

$$\mathbb{E}[Y(w)] = \mathbb{E}[Y|W = w].$$

This requires that the distribution of unobservables, or potential outcomes, for the subpopulation of firms that were assigned $W = w$ be the same as that for the overall population of firms; a condition that holds under random assignment of W.

Discuss relation to

$$Y = h(W, X, Z, \varepsilon),$$

with $\varepsilon \perp (W, X, Z)$.

The full assumption requires this equality to hold only in subpopulations homogenous in X and Z. Define

$$g(w, x, z) = \mathbb{E}[Y|W = w, X = x, Z = z],$$

denote the average output associated with input level w and characteristics x and z. Under unconfoundedness we have – among firms with identical values of X and Z – an equality between the counterfactual average output that we would observe if all firms in this subpopulation were assigned $W = w$, and the average output we observe for the subset of firms within this subpopulation that are in fact assigned $W = w$. That is

$$g(w, x, z) = \mathbb{E}[Y(w)|X = x, Z = z].$$

Assumption 2.1 has proved controversial (c.f., Imbens 2004). It holds under conditional random assignment of W to units; as would occur in an explicit experiment. However randomized allocation mechanisms are also used by administrators in some institutional settings. For example some universities match freshman roommates randomly conditional on responses in a housing questionnaire (e.g., Sacerdote 2001). This assignment mechanism is consistent with Assumption 2.1. In other settings, particularly where assignment is bureaucratic, as may be true in some educational settings, a plausible set of conditioning variables may be available. In this paper we focus upon identification and estimation under Assumption 2.1. In principle, however, the methods could be extended to accommodate other approaches to identification based upon, for example, instrumental variables.

Much of the treatment effect literature (e.g., Angrist and Krueger, 2000; Heckman, Lalonde and Smith, 2000; Manski, 1990; Imbens, 2004) has focused on the average effect of an increase in the value of the treatment. In particular, in the binary treatment case ($w \in \{0, 1\}$) interest has centered on the average treatment effect

$$\mathbb{E}_{X,Z}[g(1, X, Z) - g(0, X, Z)].$$

With continuous inputs one may be interested in the full average output function $g(w, x, z)$ (Imbens, 2000; Flores, 2005) or in its derivative with respect to the input,

$$\frac{\partial g}{\partial w}(w, x, z),$$

either at a point or averaged over some distribution of inputs and characteristics (e.g., Powell, Stock and Stoker, 1989; Hardle and Stoker, 1989).

Here we are interested in a different estimand. We focus on policies that redistribute the input W according to a rule based on the X characteristic of the unit. For example upon assignment mechanisms that match teachers of varying experience to classes of students based on their mean ability. One might assign those teachers with the most experience (highest values of W) to those classrooms with the highest ability students (highest values of X) and so on. In that case average outcomes would reflect perfect rank correlation between W and X. Alternatively, we could be interested in the average outcome if we were to assign W to be negatively perfectly rank correlated with X. A third possibility is to assign W so that it is independent of X. We are interested in the effect of such policies on the average value of the output. We refer to such effects as Aggregate Redistributional Effects (AREs).

The above reallocations are a special case of a general set of reallocation rules that fix the marginal distributions of W and X, but allow for correlation in their joint distribution. For perfect assortative matching the correlation is 1, for negative perfect assortative matching -1, and for random allocation 0. By using a bivariate normal cupola we can trace out the path between these extremes.

We wish to emphasize that there are at least two limitations to our approach. First, we focus on comparing specific assignment rules, rather than searching for the optimal assignment rule within a class. The latter problem is a particularly demanding problem in the current setting with continuously-valued inputs as the optimal assignment for each unit depends both on the characteristics of that unit as well as on the marginal distribution of characteristics in the population. When the inputs are discrete-valued both the problems of inference for a specific rule as well as the problem of finding the optimal rule become considerably more tractable. In that case any rule, corresponding to a joint distribution of the inputs, is characterized by a finite number of parameters. Maximizing estimated average output over all rules evaluated will then generally lead to the optimal rule. Graham, Imbens and Ridder (2006a) provide a detailed discussion for the binary case.

A second limitation is that of this class of assignment rules leaves the marginal distribution of inputs unchanged. This latter restriction is perfectly appropriate in cases where the inputs are indivisible, as, for example, in the social interactions and educational examples. In other cases one need not be restricted to such assignment rules. A richer class of estimands would allow for assignment rules that maintain some aspects of the marginal distribution of inputs but not others. A particularly interesting class consists of assignment rules that maintain the average (and thus total) level of the input, but allow for its arbitrary distribution across units. This can be interpreted as assignment rules that 'balance the budget'. In such cases one might assign the maximum level of the input to some subpopulation and the minimum level of the input to the remainder of the population. Finally, one may wish to consider arbitrary decision rules where each unit can be assigned any level of the input within a set. In that case interesting questions include both the optimal assignment rule as a function of unit-level characteristics as well as average outcomes of specific assignment rules. In the binary treatment case such problems have been studied by Dehejia (2005), Manski (2004), and Hirano and Porter (2005).

We consider the following four estimands that include four benchmark assignment rules. All leave the marginal distribution of inputs unchanged. This obviously does not exhaust the possibilities within this class. Many other assignment rules are possible, with corresponding estimands. However, the estimands we consider here include focal assignments, indicate of the range of possibilities, and capture many of the methodological issues involved.

3 Aggregate Redistributional Effects

3.1 Positive and Negative Assortive Matching

The first estimand we consider is expected average outcome given perfect assortative matching of W on X conditional on Z:

$$\beta^{\text{pam}} = \mathbb{E}[g(F^{-1}_{W|Z}(F_{X|Z}(X|Z)|Z), X, Z)], \tag{3.1}$$

where $F_{X|Z}(X|Z)$ denotes the conditional CDF of X given Z and $F^{-1}_{W|Z}(q|Z)$ is the quantile of order $q \in [0,1]$ associated with the conditional distribution of W given Z (i.e., $F^{-1}_{W|Z}(q|Z)$ is a conditional quantile function). Therefore $F^{-1}_{W|Z}(F_{X|Z}(X|Z)|Z)$ computes a unit's location on the conditional CDF of X given Z and reassigns it the corresponding quantile of the conditional distribution of W given Z. Thus among units with the same realization of Z, those with the highest value of X are reassigned the highest value of W and so on.

The focus on reallocations within subpopulations defined by Z, as opposed to population-wide reallocations, is because the average outcome effects of such reallocations solely reflect complementarity or substitutability between W and X.

To see why this is the case consider the alternative estimand

$$\beta^{\text{pam2}} = \mathbb{E}\left[g\left(F_W^{-1}(F_X(X), X, Z\right)\right]. \tag{3.2}$$

This gives average output associated with population-wide perfect assortative matching of W on X. If, for example, X and Z are correlated, then this reallocation, in addition to altering the joint distribution of W and X, will alter the joint distribution of W and Z. Say Z is also a scalar and is positively correlated with X. Population-wide positive assortative matching will induce perfect rank correlated between W and X, but it will also increase the degree of correlation between W and Z. This complicates interpretation when $g(w, x, z)$ may be non-separable in w and z as well as w and x.

An example helps to clarify the issues involved. Let W denote an observable measure of teacher quality, X mean (beginning-of-year) achievement in a classroom, and Z the fraction of the classroom that is female. If begining-of-year achievement varies with gender, then X and Z will be correlated. A reallocation that assigns high quality teachers to high achievement classrooms, will also tend to assign such teachers to classrooms will an above average fraction of females. Average achievement increases observed after implementing such a reallocation may reflect complementarity between teacher quality and begining-of-year student achievement or it may be that the effects of changes in teacher quality vary with gender and that, conditional on gender, their is no complementarity between teacher quality and achievement. By focusing on reallocations of teachers across classrooms with similar gender mixes, but varying baseline achievement, (3.1) provides a more direct avenue to learning about complementarity.[2]

Both (3.1) and (3.2) may be policy relevant, depending on the circumstances, and both are identified under Assumption 2.1. Under the additional assumption that

$$g(w, x, z) = g_1(w, x) + g_2(z),$$

the estimands, while associated with different reallocations, also have the same basic interpretation. Here we nonetheless focus upon (3.1), although all of our results extend naturally and directly to (3.2).

Our second estimand is the expected average outcome given negative assortative matching:

$$\beta^{\text{nam}} = \mathbb{E}[g(F_{W|Z}^{-1}(1 - F_{X|Z}(X|Z)|Z), X, Z)]. \tag{3.3}$$

If, within subpopulations homogenous in Z, W and X are everywhere complements, then the difference $\beta^{\text{pam}} - \beta^{\text{nam}}$ provides a measure of the strength input complementarity. When $g(\cdot)$ is not supermodular interpretation of this difference is not straightforward. In Section **??** below we present a measure of 'local' (relative to the status quo allocation) complementarity between X and W.

3.2 Correlated Matching

Average output under the *status quo* allocation is given by

$$\beta^{\text{sq}} = \mathbb{E}[Y] = \mathbb{E}[g(W, X, Z)],$$

[2]We make the connection to complementarity more explicit in Section **??** below.

while average output under the random matching allocation is given by

$$\beta^{\mathrm{rm}} = \int_z \left[\int_x \int_w g(w,x,z) \mathrm{d}F_{W|Z}(w|z) \mathrm{d}F_{X|Z}(x|z) \right] \mathrm{d}F_Z(z).$$

This last estimand gives average output when W and X are independently assigned within subpopulations.

The perfect positive and negative assortative allocations are focal allocations, being emphasized in theoretical research (e.g., Becker and Murphy 2000). The status quo and random matching allocations are similarly natural benchmarks. However these allocations are just four among the class of feasible allocations. This class is comprised of all joint distributions of inputs consistent with fixed marginal distributions (within subpopulations homogenous in Z). As noted in the introduction, if the inputs are continuously distributed this class of joint distributions is very large. For this reason we only consider a subset of these joint distributions. To be specific, we concentrate on a two-parameter subset of the feasible allocations that have as special cases the negative and positive assortative matching allocations, the independent allocation, and the status quo allocation. By changing the two parameters we trace out a 'path' in two directions: further from or closer to the status quo allocation, and further from or closer to the perfect sorting allocations. Borrowing a term from the literature on cupolas, we call this class of feasible allocations comprehensive, because it contains all four focal allocations as a special case.

For the purposes of estimation, the correlated matching allocations are redefined using a truncated bivariate normal cupola. The truncation ensures that the denominator in the weights of the correlated matching ARE are bounded from 0, so that we do not require trimming. The bivariate standard normal PDF is

$$\phi(x_1, x_2; \rho) = \frac{1}{2\pi\sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)}(x_1^2 - 2\rho x_1 x_2 + x_2^2)},$$

with a corresponding joint CDF denoted by $\Phi(x_1, x_2; \rho)$. Observe that

$$\Pr(-c < x_1 \leq c, -c < x_2 \leq c) = \Phi(c, c; \rho) - \Phi(c, -c; \rho) - [\Phi(-c, c; \rho) - \Phi(-c, -c; \rho)],$$

so that the truncated standard bivariate normal PDF is given by

$$\phi_c(x_1, x_2; \rho) = \frac{\phi(x_1, x_2; \rho)}{\Phi(c, c; \rho) - \Phi(c, -c; \rho) - [\Phi(-c, c; \rho) - \Phi(-c, -c; \rho)]}$$

with $-c < x_1, x_2 \leq c$. Denote the truncated bivariate CDF by Φ_c.

The truncated normal bivariate CDF gives a comprehensive cupola, because the corresponding joint CDF

$$H_{W,X}(w, x) = \Phi_c\left(\Phi_c^{-1}(F_W(w)), \Phi_c^{-1}(F_X(x)); \rho\right)$$

has marginal CDFs equal to $H_{W,X}(w, \infty) = F_W(w)$ and $H_{W,X}(\infty, x) = F_X(x)$, it reaches the upper and lower Fréchet bounds on the joint CDF for $\rho = 1$ and $\rho = -1$, respectively, and it has independent W, X as a special case for $\rho = 0$.

To obtain an estimate of $\beta^{\mathrm{cm}}(\rho, \tau)$ we note that joint PDF associated with $H_{W,X}(w, x)$ equals

$$h_{W,X}(w, x) = \phi_c\left(\Phi_c^{-1}(F_W(w)), \Phi_c^{-1}(F_X(x)); \rho\right) \frac{f_W(w) f_X(x)}{\phi_c\left(\Phi_c^{-1}(F_W(w))\right) \phi_c\left(\Phi_c^{-1}(F_X(x))\right)},$$

and hence that $\beta^{\mathrm{cm}}(\rho,0)$, redefined in terms of the truncated normal, is given by

$$\beta^{\mathrm{cm}}(\rho,0)=\int_{x,z}\int_{w}g(w,x,z)\frac{\phi_c\left(\Phi_c^{-1}(F_W(w)),\Phi_c^{-1}(F_X(x));\rho\right)}{\phi_c\left(\Phi_c^{-1}(F_W(w))\right)\phi_c\left(\Phi_c^{-1}(F_X(x))\right)}f_W(w)f_{X,Z}(x,z)\mathrm{d}w\mathrm{d}x\mathrm{d}z.$$

Average output under the correlated matching allocation is given by

$$\beta^{\mathrm{cm}}(\rho,\tau)=\tau\cdot\mathbb{E}[Y]+(1-\tau)\cdot\int g(w,x,z)\mathrm{d}\Phi\left(\Phi^{-1}(F_{W|Z}(w|z)),\Phi^{-1}(F_{X|Z}(x|z));\rho\right)F_Z(z),\quad(3.4)$$

for $\tau\in[0,1]$ and $\rho\in(-1,1)$.

The case with $\tau=1$ corresponds to the *status quo*:

$$\beta^{\mathrm{sq}}=\beta^{\mathrm{cm}}(\rho,1)$$

The case with $\tau=\rho=0$ corresponds to random allocation of inputs within sub-populations defined by Z:

$$\beta^{\mathrm{rm}}=\beta^{\mathrm{cm}}(0,0)=\int_z\left[\int_x\int_w g(w,x,z)\mathrm{d}F_{W|Z}(w|z)\mathrm{d}F_{X|Z}(x|z)\right]\mathrm{d}F_Z(z).$$

While the cases with $\tau=0$ and $\rho\to1$ and -1 correspond respectively to the perfect positive and negative assortative matching allocations. More generally, with $\tau=0$ we allocate the inputs using a normal copula in a way that allows for arbitrary correlation between W and X indexed by the parameter ρ. In principle we could use other copulas.

3.3 Local Measures of Complementarity

A potential problem with the $\beta(\rho,\tau)$ family of estimands is that the support requirements for their precise estimation may be difficult to satisfy in practice, particularly for allocations 'distant' from the status quo. For this reason a measure of local (to the status quo) complementarity between W and X would be valuable. To this end we next characterize the mean effect associated with a 'small' increase toward either positive or negative assortative matching. The resulting estimand forms the basis of a simple test for local efficiency of the status quo allocation.

We implement our local reallocation as follows: for $\lambda\in[-1,1]$, let $W_\lambda=\lambda\cdot X+(\sqrt{1-\lambda^2})\cdot W$ be a random variable indexed by λ. The average output associated with positive assortative matching on W_λ is given by

$$\beta^{\mathrm{lr}}(\lambda)=\mathbb{E}[g(F_{W|Z}^{-1}(F_{W_\lambda|Z}(W_\lambda|Z)|Z),X,Z)].\quad(3.5)$$

For $\lambda=0$ and $\lambda=1$ we have $W_\lambda=W$ and $W_\lambda=X$ respectively and hence $\beta^{\mathrm{lr}}(0)=\beta^{\mathrm{sq}}$ and $\beta^{\mathrm{lr}}(1)=\beta^{\mathrm{pam}}$. Perfect negative assortative matching is also nested in this framework since

$$\Pr\left(-X\le-x|Z\right)=1-F_{X|Z}\left(x|Z\right),$$

and hence for $\lambda=-1$ we have $\beta^{\mathrm{lr}}(-1)=\beta^{\mathrm{nam}}$. Values of λ close to zero induce reallocations of W that are 'local' to the status quo, with $\lambda>0$ and $\lambda<0$ generating shifts toward positive and negative assortative matching respectively.

The *sign* of the effect on average outcomes associated with a small step away from the status quo and toward positive assortative matching is given by the sign of

$$\beta^{\mathrm{lc}} = \frac{\partial \beta^{\mathrm{lr}}}{\partial \lambda}(0), \tag{3.6}$$

while that associated with a small step toward negative assortative matching is given by the sign of $-\beta^{\mathrm{lc}}$.

Equation (3.6) has two alternative representations which are given in the following Lemma.

Lemma 3.1 *$\beta^{\mathrm{lc}} = \partial\beta^{lr}(0)/\partial\lambda$ has equivalent representations of*

$$\beta^{\mathrm{lc}} = \mathbb{E}\left[\frac{\partial g}{\partial w}(W,X,Z)\cdot(X - m(W,X))\right], \tag{3.7}$$

where $m(w,z) = \mathbb{E}[X|W=w, Z=z]$ and, if the support of X is bounded (i.e., $a \leq X \leq b$), of

$$\beta^{\mathrm{lc}} = \mathbb{E}\left[Var(X|W,Z)\cdot\mathbb{E}_{X|W,Z}\left[\omega(V)\frac{\partial^2 g}{\partial w \partial x}(W,X,Z)|W,Z\right]\right], \tag{3.8}$$

where $V = (W,X,Z')'$ as above and

$$\omega(W,t,Z) = \frac{1}{dF_{X|W,Z}(t|W,Z)}\frac{\mathbb{E}_{X|W,Z}[X - m(W,X)|W,Z,X\geq t]\left(1 - F_{X|W,Z}(t|W,Z)\right)}{\int_{r=a}^{r=b}\mathbb{E}_{X|W,Z}[X - m(W,X)|W,Z,X\geq r]\left(1 - F_{X|W,Z}(r|W,Z)\right)dr}$$

are weights with a population mean of 1 (i.e., $\mathbb{E}_{X|W,Z}[\omega(V)|W,Z] = 1$) and which emphasize values of $\frac{\partial^2 g}{\partial w \partial x}(W,X,Z)$ where X is near its conditional mean, $m(W,X)$.

Proof: See Appendix **??**.

Representation (3.7), as we demonstrate below, suggests a straightforward method-of-moments approach to estimating β_0^{lc}. Representation (3.8) is valuable for interpretation. Equation (3.8) demonstrates that a test of $H_0 : \beta^{\mathrm{lc}} = 0$ is a test of the the null of no complementarity or substitutability between W and X. If $\beta^{\mathrm{lc}} > 0$, then in the 'vicinity of the status quo' W and X are complements; if $\beta^{\mathrm{lc}} < 0$ they are substitutes. The precise meaning of the 'vicinity of the status quo' is implicit in the form of the weight function $\omega(V)$.

Deviations of β^{lc} from zero imply that the status quo allocation does not maximize average outcomes. For $\beta^{\mathrm{lc}} > 0$ a shift toward positive assortative matching will raise average outcomes, while for $\beta^{\mathrm{lc}} < 0$ a shift toward negative assortative matching will do so. Lemma 3.1 therefore provides the basis of a test for whether the status quo allocation is locally efficient.

4 Estimation and inference with continuously-valued inputs

In this section we discuss estimation and inference.

4.1 Estimating the Production Function

$$\hat{g}(w,x,z) = .$$

Lemma 4.1 (Properties of $\hat{g}(w,x,z)$)
Suppose Assumptions XXX hold. Then

4.2 Estimation and Inference for $\widehat{\beta}^{\text{pam}}$ and $\widehat{\beta}^{\text{nam}}$

In this section we present feasible estimators for the perfect positive, negative and correlated matching estimands and state their large sample properties. While the $\beta^{\text{cm}}(\rho, \tau)$ can be estimated at standard parametric rates for $\tau \in [0,1]$ and $\rho \in (-1,1)$. Average output under the perfect positive and negative assortative matching allocations, β^{pam} and β^{nam}, can only be estimated an nonparametric rates. We therefore consider inference separately for the two cases.

[NOTE: There is a disjunct between what follows and what was stated in Section 3 above. In particular we need to use estimators of the conditional CDFs $F_{X|Z}(X|Z)$ and $F_{W|Z}(W|Z)$ as well as the conditional quantile function $F_{W|Z}^{-1}(p|Z)$. There are several off the shelf possibilities here. For now I have proceeded with using the unconditional estimators as before. Thus these estimators calculate average output under "population wide" reallocations not realloactions within subpopulations homogenous in Z.]

The estimator for the status quo average outcome is just the average sample outcome, $\hat{\beta}_{sq} = \sum_i Y_i/N$. This is efficient and inference is entirely standard. For the other estimators we first need to estimate the regression function $g(w,x,z)$. We estimate $g(w,x,z)$ using nonparametric methods. We use kernel methods, although series estimators could also be used. For a kernel $K(u)$, with $u \in \mathbb{R}^{K+2}$, bandwidth b, and with $V_i = (W_i, X_i, Z_i')'$ and $v = (w, x, z')'$, we have

$$\hat{g}(w,x,z) = \frac{\sum_{i=1}^N Y_i \cdot K((v - V_i)/b)}{\sum_{i=1}^N K((v - V_i)/b)}.$$

In the sequel we use the notation $K_b(v) = \frac{1}{b^{K+2}} K\left(\frac{v}{b}\right)$.

Each of our estimators also require plug-in estimates of either $F_X(x)$ or $F_W(w)$ or both. For these objects we use the empirical CDFs

$$\hat{F}_X(x) = \frac{1}{N}\sum_{i=1}^N 1\{X_i \le x\}, \qquad \hat{F}_W(w) = \frac{1}{N}\sum_{i=1}^N 1\{W_i \le w\}.$$

For the quantile function $F_W^{-1}(q)$, required for the perfect positive and negative matching cases, we use the inverse of the empirical distribution function of W, i.e.,

$$\hat{F}_W^{-1}(q) = \inf_{w \in \mathbb{W}} 1\{\hat{F}_W(w) \ge q\}.$$

We then estimate β^{pam} and β^{nam} by the analog estimators

$$\widehat{\beta}^{\text{pam}} = \frac{1}{N}\sum_{i=1}^N \hat{g}\left(\hat{F}_W^{-1}(\hat{F}_X(X_i)), X_i, Z_i\right),$$

and

$$\widehat{\beta}^{\text{nam}} = \frac{1}{N}\sum_{i=1}^N \hat{g}\left(\hat{F}_W^{-1}(1 - \hat{F}_X(X_i)), X_i, Z_i\right).$$

In this subsection we discuss the large sample properties of $\hat{\beta}^{\text{pam}}$. The rate of convergence of $\hat{\beta}^{\text{pam}}$ to β^{pam} is slower than the regular parametric rate. This is because we estimate a nonparametric regression function with more arguments than we average over in the second stage.

Define:

$$\tilde{\beta}^{\text{pam}} = \frac{1}{N}\sum_{i=1}^{N} g\left(F_w^{-1}\left(F_X(X_i)\right), X_i\right). \tag{4.9}$$

Then $\hat{\beta}^{\text{pam}} - \tilde{\beta}^p am = O_p(N^{-1/2}b_N^{-1/2})$, and $\tilde{\beta}^p am - \beta^p am = O_p(N^{-1/2}$. However, in order to improve the performance of confidence intervals we will take into account additional terms in the asymptotic expansion beyond the leading $O_p(N^{-1/2}b_N^{-1/2})$ term. Specifically, we take into account the $O_p(N^{-1/2})$ terms.

$$\sqrt{N} \cdot \begin{pmatrix} b_N^{1/2}\left(\hat{\beta}^{\text{pam}} - \tilde{\beta}^{\text{pam}}\right) \\ \tilde{\beta}^{\text{pam}} - \beta^{\text{pam}} \end{pmatrix} \xrightarrow{d} \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \Omega\right),$$

We propose a consistent estimator $\hat{\Omega}$ for Ω. As the estimator for the variance of $N^{1/2}b_N^{1/2}(\hat{\beta}^{\text{pam}} - \beta^{\text{pam}}$ we then propose to use

$$\hat{\sigma}_\beta^2 = \begin{pmatrix} 1 \\ b_N^{1/2} \end{pmatrix}' \hat{\Omega} \begin{pmatrix} 1 \\ b_N^{1/2} \end{pmatrix}.$$

As $N \to \infty$, this converges to

$$\text{plim}_{N\to\infty}\hat{\sigma}_\beta^2 = \Omega_{11},$$

because $b_N \to 0$. Hence we could simply estimate the asymptotic variance as

$$\tilde{\sigma}_\beta^2 = \hat{\Omega}_{11}.$$

Nevertheless, it is likely that taking into account the variation in $\hat{\mu}_W$, $\hat{\mu}_X$ and $\hat{\mu}_g$ will improve the finite sample properties of the confidence intervals.

Assumption 4.1 *There are positive integers Δ and s such that $\mathcal{K}(u)$ is differentiable of order Δ, the derivatives of order Δ are Lipschitz, $\mathcal{K}(u)$ is zero outside a bounded set, $\int \mathcal{K}(u)du = 1$, and for all $j < s$, $\int \mathcal{K}(u)[\otimes_{l=1}^{j}]du = 0$.*

Assumption 4.2 (PROBABLY SUPERFLUOUS GIVEN OTHER ASSUMPTIONS) *There is a non-negative integer d and an extension of $g(x)$ to all of $\mathbb{R}^k$ that is continuously differentiable to order d on $\mathbb{R}^k$.*

Assumption 4.3 (PROBABLY SUPERFLUOUS GIVEN OTHER ASSUMPTIONS) *For $p \geq 4$, $\mathbb{E}[|Y|^p] \leq \infty$, $\mathbb{E}[|Y|^p|X = x]f_(x)$ is bounded, $\mathbb{E}[\|m(z, \beta_0, g)\|^2] < \infty$.*

Assumption 4.4 (SMOOTHNESS OF $g(w, x)$)
$g(w, x)$ is twice continuously differentiable with respect to w on $\mathbb{W} \times \mathbb{X}$.

Assumption 4.5 (DISTRIBUTION OF DATA)
(i) The support of W is $\mathbb{W}$, a compact subset of $\mathbb{R}$,
(ii) the support of X is $\mathbb{X}$, a compact subset of $\mathbb{R}$,
(iii) the joint distribution of W and X is bounded and bounded away from zero on $\mathbb{W} \times \mathbb{X}$,
(iv) the conditional expectations $\mu_4(v) = \mathbb{E}[Y^4|W = w, X = x]$ is bounded.

Assumption 4.6 *The bandwidth b_N satisfies $b_N \to 0$, $N^{-1} b_N^{-2k_1} \to 0$ $N^{2/p-1} b_N^{-k} \ln(N) \to 0$, (p is moment of Y that exists)*

First we decompose $\hat{\beta}^{\text{pam}} - \beta^{\text{pam}}$ into four parts plus a lower order remainder term. The first part corresponds to the uncertainty in $\hat{g}(\cdot, \cdot)$, the second corresponds to the uncertainty in $\hat{F}_W^{-1}(\cdot)$, the third part corresponds to the uncertainty in $\hat{F}_X(\cdot)$, and the final part corresponds to the difference between the average of $g\left(F_W^{-1}(\hat{F}_X(X_i)), X_i\right)$ and its expectation.

Define

$$g_W(w,x) = \frac{\partial g}{\partial w}(w,x), \qquad \text{and} \quad g_{WW}(w,x) = \frac{\partial^2 g}{\partial w^2}(w,x),$$

$$q_{WX}(w,x) = \frac{g_w(F_W^{-1}(F_X(x)),x)}{f_W(F_W^{-1}(F_X(x)))} \cdot \left(1\{F_W(w) \le F_X(x)\} - F_X(x)\right),$$

$$\hat{\mu}_{WX} = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} q_{WX}(W_i, X_j),$$

$$q_W(w) = \mathbb{E}[q_{WX}(w,X)], \qquad \text{and} \quad q_X(x) = \mathbb{E}[q_{WX}(W,x)],$$

$$\hat{\mu}_W = \frac{1}{N} \sum_{i=1}^{N} q_W(W_i),$$

$$r_{X_1X_2}(x_1,x_2) = \frac{g_w(F_W^{-1}(F_X(x_2)),x_2)}{f_W(F_W^{-1}(F_X(x_2)))} \cdot \left(1\{x_1 \le x_2\} - F_X(x_2)\right),$$

$$\hat{\mu}_{X_1X_2} = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} r_{X_1X_2}(X_i, X_j),$$

$$r_{X_1}(x) = \mathbb{E}[r_{X_1X_2}(x,X)], \qquad \text{and} \quad r_{X_2}(x) = \mathbb{E}[r_{X_1X_2}(X,x)],$$

$$\hat{\mu}_X = \frac{1}{N} \sum_{i=1}^{N} r_{X_1}(X_i).$$

Theorem 4.1 ()
Suppose Assumptions XXXX hold. Then

$$\sqrt{N} \cdot \begin{pmatrix} b_N^{1/2}\left(\hat{\beta}^{\text{pam}} - \tilde{\beta}^{\text{pam}}\right) \\ \tilde{\beta}^{\text{pam}} - \beta^{\text{pam}} \end{pmatrix} \xrightarrow{d} \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} V_{11}^{\text{pam}} & 0 \\ 0 & V_{22}^{\text{pam}} \end{pmatrix} \right),$$

where

$$V_{11}^{\text{pam}} = \mathbb{E}\Bigg[\sigma^2\left(F_W^{-1}\left(F_X(X)\right), X\right) \cdot \int_{u_1} \left(\int_{u_2} K\left(u_1 + \frac{f_X(X)}{f_W\left(F_W^{-1}\left(F_X(X)\right)\right)} \cdot u_2, u_2\right)\right)^2 du_1$$
$$\cdot f_{W|X}\left(F_W^{-1}\left(F_X(X)\right)|X\right)\Bigg],$$

and

$$V_{22}^{\text{pam}} = \mathbb{E}\left[\left(q_W(W) + r_X(X) + g(W,X) - \beta^{\text{pam}}\right)^2\right].$$

Define

$$\hat{V}_{11}^{\text{pam}} =,$$

and

$$\hat{V}_{22}^{\text{pam}} =,$$

Theorem 4.2 ()
Suppose XXX hold. Then

$$\hat{V}_{11}^{\text{pam}} \xrightarrow{p} V_{11},$$

and

$$\hat{V}_{22}^{\text{pam}} \xrightarrow{p} V_{22}.$$

Similar theorems for β^{nam}:
Define

$$\tilde{\beta}^{n} am =,$$

where

$$V_{11}^{\text{nam}} = \mathbb{E}\Bigg[\sigma^2\left(F_W^{-1}\left(F_X(X)\right), X\right) \cdot \int_{u_1}\left(\int_{u_2} K\left(u_1 + \frac{f_X(X)}{f_W\left(F_W^{-1}\left(F_X(X)\right)\right)} \cdot u_2, u_2\right)\right)^2 du_1$$
$$\cdot f_{W|X}\left(F_W^{-1}\left(F_X(X)\right)|X\right)\Bigg],$$

and

$$V_{22}^{\text{nam}} = \mathbb{E}\left[\left(q_W(W) + r_X(X) + g(W,X) - \beta^{\text{pam}}\right)^2\right].$$

$$\hat{V}_{11}^{\text{nam}} =,$$

and

$$\hat{V}_{22}^{\text{nam}} =,$$

Theorem 4.3 ()
Suppose Assumptions XXXX hold. Then

$$\sqrt{N} \cdot \begin{pmatrix} b_N^{1/2}\left(\hat{\beta}^{\text{nam}} - \tilde{\beta}^{\text{nam}}\right) \\ \tilde{\beta}^{\text{nam}} - \beta^{\text{nam}} \end{pmatrix} \xrightarrow{d} \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} V_{11}^{\text{nam}} & 0 \\ 0 & V_{22}^{\text{nam}} \end{pmatrix}\right).$$

Theorem 4.4 ()
Suppose XXX hold. Then

$$\hat{V}_{11}^{\text{nam}} \xrightarrow{p} V_{11},$$

and

$$\hat{V}_{22}^{\text{nam}} \xrightarrow{p} V_{22}.$$

4.3 Estimation and Inference for $\beta^{\text{cm}}(\rho,\tau)$

Replacing the integrals with sums over the empirical distribution we get the analog estimator

$$\widehat{\beta}^{\text{cm}}(\rho,0) = \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}\hat{g}(W_i,X_j,Z_j)\frac{\phi_c\left(\Phi_c^{-1}(\hat{F}_W(W_i)),\Phi_c^{-1}(\hat{F}_X(X_j));\rho\right)}{\phi_c\left(\Phi_c^{-1}(\hat{F}_W(W_i))\right)\phi_c\left(\Phi_c^{-1}(\hat{F}_X(X_j))\right)}.$$

Observe that if $\rho = 0$ (independent matching) the ratio of densities on the right hand side is equal to 1.

For $\tau > 0$, the $\beta^{\text{cm}}(\rho,\tau)$ estimand is a convex combination of average output under the status quo and a correlated matching allocation. The corresponding sample analog is

$$\widehat{\beta}^{\text{cm}}(\rho,\tau) = \tau\cdot\widehat{\beta}^{\text{sq}} + (1-\tau)\cdot\widehat{\beta}^{\text{cm}}(\rho,0).$$

This estimator is linear in the nonparametric regression estimator $\hat{g}$ and nonlinear in the empirical CDFs of X and W. This structure simplifies the asymptotic analysis.

A useful and insightful representation of $\beta^{\text{cm}}(\rho,0)$ is as an average of partial means (c.f., Newey 1994). This representation provides intuition both about the structure of the estimand as well as its large sample properties. Fixing W at $W = w$ but averaging over the joint distribution of X and Z we get the partial mean:

$$\eta\left(w\right) = \mathbb{E}_{X,Z}\left[g(w,X,Z)\times d(w,X)\right], \tag{4.10}$$

where

$$d(w,x) = \frac{\phi_c(\Phi_c^{-1}(F_W(w)),\Phi_c^{-1}(F_X(x));\rho)}{\phi_c(\Phi_c^{-1}(F_W(w)))\phi_c(\Phi_c^{-1}(F_X(x)))}. \tag{4.11}$$

Observe that (4.10) is a weighted averaged of the production function over the joint distribution of X and Z holding the value of the input to be reallocated W fixed at $W = w$. The weight function $d(w,X)$ depends upon the truncated normal cupola. In particular, the weights give greater emphasis to realizations of $g(w,X,Z)$ that are associated with values of X that will be assigned a value of W close to w as part of the correlated matching reallocation. Thus (4.10) equals the average post-reallocation output for those firms being assigned $W = w$. To give a concrete example (4.10) is the post-reallocation expected achievement of those classrooms that will be assigned a teacher of quality $W = w$.

Equation (4.10) also highlights the value of using the truncated normal copula. Doing so ensures that the denominators of the copula 'weights' in (4.10) are bounded from zero. The copula weights thus play the role similar to fixed trimming weights used by Newey (1994).

If we average these partial means over the marginal distribution of W we get $\beta^{\text{cm}}(\rho,0)$, since

$$\beta^{\text{cm}}(\rho,0) = \mathbb{E}_W\left[\eta\left(W\right)\right],$$

yielding average output under the correlated matching reallocation.

From the above discussion it is clear that our correlated matching estimator can be viewed as a semiparametric two-step method-of-moments estimator with a moment function of

$$m(Y,W,\beta^{\text{cm}}(\rho,\tau),\eta\left(W\right)) = \tau Y + (1-\tau)\,\eta\left(W\right) - \beta^{\text{cm}}(\rho,\tau).$$

Our estimator, $\widehat{\beta}^{\text{cm}}(\rho, \tau)$, is the feasible GMM estimator based upon the above moment function after replacing the partial mean (4.10) with a consistent estimate. While the above representation is less useful for deriving the asymptotic properties of $\widehat{\beta}^{\text{cm}}(\rho, \tau)$ it does provide some insight as to why we are able to achievement parametric rates of convergence.

Define

$$
\begin{aligned}
e_W(w,x) &= \frac{\rho\phi_c(\Phi_c^{-1}(F_W(w)), \Phi_c^{-1}(F_X(x)); \rho)}{(1-\rho^2)\phi_c(\Phi_c^{-1}(F_W(w)))^2\phi_c(\Phi_c^{-1}(\widehat{F}_X(x)))} \times \qquad (4.12)\\
&\quad \left[\Phi_c^{-1}(F_X(x)) - \rho\Phi_c^{-1}(F_W(w))\right]\\
e_X(w,x) &= \frac{\rho\phi_c(\Phi_c^{-1}(F_W(w)), \Phi_c^{-1}(F_X(x)); \rho)}{(1-\rho^2)\phi_c(\Phi_c^{-1}(F_W(w)))\phi_c(\Phi_c^{-1}(\widehat{F}_X(x)))^2} \times \qquad (4.13)\\
&\quad \left[\Phi_c^{-1}(F_W(w)) - \rho\Phi_c^{-1}(F_X(X_k))\right].
\end{aligned}
$$

In order to state a formal result we need the following assumptions

Assumption 4.7 *Let $v = (w\ x\ z')'$. The function $K(v)$ is bounded on a bounded set $\mathcal{V}$ and $K(v) = 0$ for $v \in \mathcal{V}^c$. Also K is a kernel of order S*

$$\int_{\mathcal{V}} K(v)dv = 1 \qquad \int_{\mathcal{V}} v^s K(v)dv = 0$$

for $s = 1, \ldots, S$ with $v^s = \prod_{s_1 \geq 0, \ldots, s_{K+2} \geq 0, s_1 + \cdots s_{K+2} = s} v_1^{s_1} \cdots v_{K+2}^{s_{K+2}}$

Assumption 4.8 *The joint density $f_{W,X,Z}(w, x, z)$ has compact support $\mathcal{W} \times \mathcal{X} \times \mathcal{Z}$ and the density is bounded from 0 and ∞ on this support.*

Assumption 4.9 *The function $g(w, x, z) = \mathbb{E}[Y|W = w, X = x, Z = z]$ that is defined on $\mathcal{W} \times \mathcal{X} \times \mathcal{Z}$ can be extended to $\Re^{K+2}$ such that it is S times continuously differentiable and the S-th derivative is bounded on $\Re^{K+2}$.*

Assumption 4.10 $\mathbb{E}[Y^2|W, X, Z]$ *is bounded on $\mathcal{W} \times \mathcal{X} \times \mathcal{Z}$.*

Assumption 4.11 *The bandwidth sequence is such that as $N \to \infty$*

$$\frac{N^{\frac{1}{4}}}{\sqrt{\ln N}} b_N^{\frac{K}{2}+1} \to \infty, \qquad \sqrt{N} b_N^{S(K+2)} \to 0.$$

Theorem 4.5 *If assumptions 4.7-4.11 hold, then*

$$\widehat{\beta}^{\text{cm}}(\rho, \tau) \xrightarrow{p} \beta^{\text{cm}}(\rho, \tau)$$

and

$$\sqrt{N}(\widehat{\beta}^{\text{cm}}(\rho, \tau) - \beta^{\text{cm}}(\rho, \tau)) \xrightarrow{d} \mathcal{N}(0, V^{\text{cm}}),$$

where

$$V^{\text{cm}} = \mathbb{E}\left[(\tau(Y - \beta^{\text{sq}}) + (1-\tau)\,\psi(Y, W, X, Z))^2\right],$$

and

$$\psi(y,w,x,z) = \mathbb{E}\left[g(W,x,z)d(W,x)\right] + \mathbb{E}\left[g(w,X,Z)d(w,X)\right] - 2\beta^{\mathrm{cm}}(\rho,0) \qquad (4.14)$$
$$+\frac{f_W(w)}{f_{W|XZ}(w|x,z)}(y-g(w,x,z))d(w,x)$$
$$+\mathbb{E}\left[e_W(W,X)g(X,W,Z)(I(w\le W)-F_W(W))\right]$$
$$+\mathbb{E}\left[e_W(W,X)g(W,X,Z)(I(x\le X)-F_X(X))\right].$$

Proof: All proofs are in the Appendices

Define

$$\hat{V}^{\mathrm{cm}} = \frac{1}{N}\sum\nolimits_{i=1}^{N}(\tau(Y_i-\beta^{\mathrm{sq}}) + (1-\tau)\,\widehat{\psi}(Y_i,W_i,X_i,Z_i))^2.$$

Theorem 4.6 ()
Suppose XXX hold. Then

$$\hat{V}^{\mathrm{cm}} \xrightarrow{p} V^{\mathrm{cm}}.$$

4.4 Estimation and Inference for β^{lc}

Estimation of β^{lc} proceeds in two-steps. First we estimate $g\,(w,x,z)$ and $m\,(w,z)$ using kernel methods as in Section 4. In the second step we estimate β^{lc} by method-of-moments using the sample analog of the moment condition

$$\mathbb{E}\left[m\left(Y,V,\beta_0^{\mathrm{lc}},g,m\right)\right] = \mathbb{E}\left[\frac{\partial}{\partial w}g\,(W,X,Z)\,(X-m\,(W,Z)) - \beta_0^{\mathrm{lc}}\right] = 0,$$

where $g\,(W,X,Z)$ and $m\,(W,Z)$ are replaced with the first step estimates, i.e.,

$$\widehat{\beta^{\mathrm{lc}}} = \frac{1}{N}\sum\nolimits_{i=1}^{N}\frac{\partial}{\partial w}\widehat{g}\,(W_i,X_i,Z_i)\times(X_i-\widehat{m}\,(W_i,Z_i)). \qquad (4.15)$$

Note that we compute $\frac{\partial}{\partial w}\widehat{g}\,(w,x,z)$ by analytically differentiating $\widehat{g}\,(w,x,z)$ with respect to w.

The asymptotic properties of $\widehat{\beta^{\mathrm{lc}}}$ are derived analogously to those of $\widehat{\beta}^{\mathrm{cm}}$ and are summarized by Theorem 4.7.

Theorem 4.7 *Under conditions 4.7 to 4.11* $\widehat{\beta^{\mathrm{lc}}}$ *is* $\sqrt{N}$ *consistent and asymptotically normal, i.e.,*

$$\widehat{\beta^{\mathrm{lc}}} \xrightarrow{p} \beta^{\mathrm{lc}}$$

and

$$\sqrt{N}(\widehat{\beta^{\mathrm{lc}}} - \beta_0^{\mathrm{lc}}) \xrightarrow{d} \mathcal{N}(0,V^{\mathrm{lc}}),$$

where

$$V^{\mathrm{lc}} = Var\,(\psi)$$

with

$$\psi(y,v) = m\left(y, v, \beta_0^{\mathrm{lc}}, g, m\right) + \delta\left(y, v\right),$$

and

$$\begin{aligned}\delta\left(Y,V\right) = & -\frac{1}{f_{W,X,Z}\left(W,X,Z\right)}\frac{\partial f_{W,X,Z}\left(W,X,Z\right)}{\partial W}\left(Y - g\left(W,X,Z\right)\right)\left(X - m\left(W,Z\right)\right) \\ & -\frac{\partial m\left(W,Z\right)}{\partial W}\left(Y - g\left(W,X,Z\right)\right) \\ & -\mathbb{E}\left[\frac{\partial g\left(W,X,Z\right)}{\partial W}|W = w, Z = z\right]\left(X - m\left(W,Z\right)\right).\end{aligned}$$

Proof: See Appendix **??**

Theorem 4.7 follows from the fact that $\widehat{\beta^{\mathrm{lc}}}$ admits an asymptotically linear representation of

$$\widehat{\beta^{\mathrm{lc}}} = \beta^{\mathrm{lc}} + \frac{1}{N}\sum\nolimits_{i=1}^{N}\left\{m\left(Y_i, V_i, \beta^{\mathrm{lc}}, g, m\right) + \delta\left(Y_i, V_i\right)\right\} + o_p(1/\sqrt{N}). \tag{4.16}$$

If $\widehat{g}\left(w,x,z\right)$ and $\widehat{m}\left(x,z\right)$ are replaced by their population values in (**??**) the final three terms in (4.16) drop out; these terms therefore represent the effect on the moment function of replacing $g\left(w,x,z\right)$ and $m\left(x,z\right)$ with their nonparametric first step estimates. The first two capture the effect of sampling error in $\nabla_w\widehat{g}\left(w,x,z\right)$ on the large sample behavior of $m\left(Y,V,\beta^{\mathrm{lc}},g,m\right)$, while the final one captures the effect of sampling error in $\widehat{m}\left(x,z\right)$.

Define

$$\hat{V}^{\mathrm{lc}} = .$$

Theorem 4.8 ()
Suppose XXX hold. Then

$$\hat{V}^{\mathrm{lc}} \xrightarrow{p} V^{\mathrm{lc}}.$$

5 Empirical application: marital sorting and child education

To illustrate our methods in practice we present estimates of AREs from a simple setting. In particular, we consider the effect of parents' education on the education of their child. Kremer (1997) is a related application. He considers the connection between neighborhood and martial sorting in terms of years schooling and inequality in educational attainment among children. Kremer specifies a linear relation between the average level of education of parents and the years of schooling of their children. This implies that the average level of childrens' education is invariant under reallocations of parents.

We use data on 10,272 children from the NLSY to study the relation between the education of parents and the education of their children. Table 1 gives summary statistics.

It should be noted that years of education is not uniformly distributed. In the data 43% of the mothers, 35% of the fathers, and 44% of the children report that they have 12 years of education with further spikes at 16 years of education. Reported years of education vary

Table 1: Years of education NLSY; $N = 12272$

	Mean	Std. dev.
Ed. child	13.06	2.38
Ed. mother	11.20	2.87
Ed. father	11.20	3.64

Table 2: Regression of education of child on education parents; NLSY, $N = 10272$

	Coefficient	Standard err.
Constant	11.27	.19
Ed. mother	-.041	.036
Ed. father	-.077	.029
Ed. mother^2	.011	.0023
Ed. father^2	.011	.0015
Ed. mother $\times$ Ed. father	.0014	.0029
R^2	.22	

between 1 and 20. A regression of a child's years of schooling on that of their mother and father (see Table 2) shows that the interaction effect is not significant. The relation is nonlinear however, so that reallocations of parents may affect the average level of child education.

In an Appendix we discuss the extension of the theoretical results from the previous sections to the case with discrete covariates.

Inspection of the average level of child education cross-classified by parent education shows that a child's educational attainment tends to be high if her mother has a high level of education and her father has a low level of education relative to cases where her mother has a low level of education and her father a high level of education. This asymmetry is not captured by the interaction term.

Instead of trying more complicated regression models we directly estimate the average education of children under correlated matching. Table 3 gives the average level for selected values of ρ (τ is set equal to zero throughout). The figure reports the same levels and also gives the error bands. The standard errors are computed by the delta method (see Appendix **??**). Note that in this application we have no Z variables, i.e. we assume rather unrealistically that the status quo assignment is not selective.

Figure 1: Average years of education child given correlated sorting; 95% error bands

Table 3: Average education given correlated (ρ) sorting

ρ	$\hat{\beta}_{cs}$	Std($\hat{\beta}_{cs}$)
-.99	11.5	.069
-.8	11.7	.048
-.6	11.9	.040
-.4	12.1	.037
-.2	12.4	.034
0.	12.6	.033
.2	12.8	.031
.4	12.9	.030
.6	13.0	.029
.8	13.0	.029
.99	13.1	.039

6 Conclusions

[TO BE COMPLETED]

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