Testing and estimating sibling interaction effects in obesity: An extension of the sibling difference framework

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Preliminary and Incomplete

December 17, 2011

Abstract

Building on sibling difference regressions, a new IV strategy for estimating heterogenous interaction effects in obesity is proposed. Identification depends on a testable restriction: standardized direct responses to variations in own covariates differ across different types of siblings. The sibling difference model is a testable special case. Using the NLSY79 children dataset, the null hypothesis of the sibling difference model of no sibling interaction effect or contextual effect on weight or BMI is not rejected using a specification test which is simple to implement. However, when we estimate the more general model we find small but statistically significant peer effects. Brothers are estimated to have a small negative reaction to an increase in their siblings' obesity whereas sisters have a small positive reaction.

In many countries, including the United States, the fraction of the population who are obese has risen significantly in recent decades.[1,2] Childhood obesity has also concurrently risen (Anderson and Butcher 2006). This rise in obesity has severe health and economic consequences for society (e.g. Colditz 1999; Visscher and Seidell 2001). Although obesity has a quantitatively significant genetic component, many researchers believe that the recent rapid rise in obesity across countries is primarily due to behavioral considerations.[3]

In an influential paper using observational data, Christakis and Fowler 2007 argued that obesity also has a social interaction component: If one's peers become obese, one is also more likely to become obese. Their methodology has been criticized (e.g. Cohen-Cole and Fletcher 2008a; 2008b). In view of the social cost of obesity and how it responds to behavioral factors, it is important to continue to develop different methodologies for detecting whether there are social interactions effects in obesity using observational data.

The objective of this paper is to estimate sibling interaction effects in childhood obesity using observational data. Since Manski 1993, researchers know that the correlation in siblings' behaviors is due to interaction effects as well as observed (contextual effects) and unobserved factors common to the family. The unobserved common family effects make it difficult to identify the interaction effects without additional identifying restriction.[4,5] A standard approach to deal with the identification problem is to instrument for the behavior of the sibling (e.g. Oettinger 2000). Due to the difficulty of coming up with valid instruments, we are not aware of any such study on estimating sibling interaction effects on obesity.[6]

Abstracting from sibling interaction effects, there is an active literature using sibling and twin difference regressions to estimate the effect of own covariates on behavior. These sibling difference regressions have been used to study the effects of birth order, gender, birth weight, neighborhoods, family structure, parental employment, age of immigration, etc. on a child's schooling, earnings or other outcomes.[7] Explicitly or implictly, this literature makes three

[1]A measure of individual obesity is when the Body Mass Index ($BMI = \frac{kg}{(height\ in\ m)^2}$) exceeds 30.

[2]Antipatis and Gill 2001; Bliech, et. al. 2007; Chou, et. al. 2002.

[3]Rashad, Grossman and Chou 2006 argued that the rise in the labor force participation rate of women led to more consumption of fast food which in turned led to a rise in obesity. Cutler, et. al. 2003 made a related point on the increasing availability of commercially prepared foods which have higher calories. Rashad and Grossman 2004 is a survey.

[4]Carman and Kooreman (2010) provide an exposition specific to estimating social interaction effects on obesity.

[5]Blume, et. al. 2010 surveys different methods developed to estimate peer interaction effects since Manski.

[6]In an innovative paper, Fletcher and Lehrer 2011 used within family variation in genetic markers as instruments for obesity to estimate the effects of own obesity on other individual outcomes. We leave the use of these genetic markers in our context to future research.

[7]E.g. Altonji and Dunn 2000; Behrman 1997; Behrman and Taubman 1986; Black, et. al. 2005; Black, et. al. 2007; Bőhlmark 2008; Bommier and Lambert 2004; Chen, et. al. 2009; Emerson and Souza 2008; Ermisch, et. al. 2004; Lindert 1977; Ota and Moffatt 2007; Page and Solon 2003; Tenikue and Verheyden 2010.

assumptions:[8]

SD1. Sibling differences in own covariates are orthogonal to differences in the unobserved common family factors.

SD2. Siblings' covariates do not directly affect own behavior.

SD3. There is no sibling interaction effect.

With these three assumptions, sibling difference regressions are used to obtain consistent estimates of the direct effects of own covariates on behavior.

Building on sibling difference regressions, this paper considers a new instrumental variable (IV) strategy for estimating sibling interaction effects in the absence of variables that are uncorrelated with the unobserved family factors to use as instrumental variable candidates. We require a strengthening of assumption SD1 to assumption:

A1. Sibling differences in own covariates are orthogonal to the levels of unobserved common family factors.

We add two assumptions:

A2. Contextual effects are either absent or are orthogonal to sibling differences in own covariates

A3. Standardized responses to variations in own covariates differ for different observable types of siblings.

With these three assumptions, we construct valid instrumental variable candidates from covariates that are correlated to unobserved common family factors. In general, the sibling interaction effects model is identified. So we can dispense with assumption SD3 as needed. We can also relax somewhat assumption SD2.

Like assumption SD1 of the sibling difference literature, our assumption A1 is maintained and untestable without additional data.[9] With A1, we can test assumptions SD2 and SD3 which are necessary for a coherent interpretation of sibling difference regressions. With A1- A3, we can estimate a model of sibling interaction effects in which an important special case, the sibling difference model, is nested.

Assumption A2 is slightly weaker than SD2. It allows for the possibility that the covariates satisfy a certain symmetry property, in which case the remaining parameters can be identified regardless of the presence or absence of contextual effects. If this symmetry property fails, however, we can follow the siblling difference literature and simply set the contextual effects to zero.

[8] A careful statement of the methodology is in Ermish, Fancesconi and Pevalin 2004.

[9] Fletcher and Lehrer 2011) show that assumption SD1 is testable with valid instruments for the covariates of interest in a sibling difference regression. In general, such instruments are not available which is the primary reason for the sibling difference literature.

Assumption A3 is the identification condition for our estimator. It is necessary and sufficient to guarantee that our instruments are not orthogonal to the covariate on the peer effect coefficient in our estimating equation. If it fails, we lose identification. It can be stated in terms of the rank of a matrix involving observables, so we can and do test A3. However, having a more primitive statement of the rank condition allows us to see what's driving the identification and to recognize a priori those environments where identification can be expected to be weak or even fail. For example, it is easy to see that the standard (Manski) linear interaction effects model with i.i.d. data and common parameters violates assumption A3. Intuitively, heterogeneity in the distribution of covariates across different observable types of siblings or their response coefficients aids identification because it generates more distinct observable moment conditions than additional parameters, enough for identification.[10]

Most papers on estimating peer effects estimate one peer effect parameter. We focus on estimating gender specific interaction coefficients, one for each gender. We can also estimate sibling interaction effects which depend on the specific observable types of the pair of siblings under consideration. In the case of gender, we can estimate up to four gender interaction effects which depend on the pair specific gender interaction.

We estimate sibling interaction effects on weight and BMI using the NLSY79 adults and children (CNLSY) datasets (**NB: In this draft, we only report results from the CNLSY). Each pair of biological siblings closest in ages are considered a separate sibling pair. Our two observable types are gender: male and female. In other words, we are assuming (and testing) assumption A3 for brothers versus sisters. Own covariates include age, height and birth weight in the child sample, and their interactions with age.

Following Cohen-Cole and Fletcher 2008a, we first do a placebo test by estimating a sibling interaction effects model of own height. An individual's height is determined primarily by genetic and environmental factors. Controlling for common family factors and own covariates, there should be no sibling interaction effect on height nor a direct effect of a sibling's covariates on own height.

After investigating the presence of sibling interaction effect on height, we next investigate the presence of sibling interaction effects on weight and BMI.

After sample selection rules detailed below, we end up with 1810 sibling pairs from the CNLSY. The correlation in weight between siblings is 0.73. The question is whether sibling interaction effects account for much of this correlation as opposed to common genetic and family factors. The correlation in BMI between sibling is 0.37. Since BMI is proportional to weight divided by the square of height, this correction for height, which is not subject to sibling interaction effect, already halves the correlation in obesity between siblings.

First in all cases, whether for height, weight or BMI, assumption A3 is not rejected at p-values below 0.0001. Thus there is enough variation across gender

[10]The extra observable moment conditions have potential wider applicability than our specific instrumental variable approach.

in standardized own responses in our dataset to use our methodology for our dependent variables.[11]

Based on our analysis, we cannot reject the sibling difference model that there is no sibling interaction or contextual effect on own height. When we estimated sibling interaction effects by gender using a two-step procedure, we obtained imprecisely estimated small negative interaction elasticities (>-0.03). Thus there was little or no evidence against the hypothesis that there is not sibling interaction effect on height.[12]

We then tested the sibling difference model for both weight and BMI. There was little evidence to reject the sibling difference model for weight or BMI. In other words, there was little evidence against no sibling interaction effect and no contextual effect.

When we estimated sibling interaction effects by gender, brothers have a small negative reaction to their sibling's weight gain whereas sisters have a small positive reaction to their sibling's weight gain. Negative estimates may be due to competition for food within a family and or averse response by a child to their sibling's change in weight.

When we use BMI as a dependent variable, the point estimates of own effects were significantly less precise, in some cases. Our estimates of the sibling interaction effects were implausibly large and precisely estimated. Since BMI imposes the restriction that the elasticity of weight with respect to height is 2, it may be the case that the model for BMI is misspecified. Another reason for the discrepancy between the results from weight and height is that for weight, we used height and its interaction with age as covariates which have significant explanatory power. For BMI, we used birth weight and its interaction with age as covariates which has less explanatory power.

In summary, there is little evidence against the sibling difference model for weight or BMI. When we estimate sibling interaction effects by gender on weight, our estimates are quantitatively small, negative for brothers and positive for sisters. While not the main focus of their paper, Christakis and Fowler 2007 estimated a positive sibling interaction effect for obesity. Our estimates do not support their finding.

There are few studies that estimate sibling interaction effects with other dependent variables using observational data.[13] Oettinger 2000 studies sibling interaction effects in schooling by birth order using standard instrumental variable technique. Also using the 79 NLSY, he finds that the schooling attainment of older siblings affect the younger siblings but not vice versa. Another paper is Altonji, Cattan and Ware 2010. They use a dynamic correlated random

[11] This is not the case for the NLSY dataset and other dependent variables. We were unable to get precise estimates of sibling interaction effects on earnings or schooling attainment with the sample sizes available. We also could not estimate precise sibling interaction effects on weight or BMI for adults in the NLSY.

[12] We obtain curious results, however, using GMM estimation that we are still working to understand. So, we summarize in this section only our empirical results based on our two-step estimator.

[13] Recents studies use field experiments to estimate the sibling peer effects in schooling attainment (E.g. Barrera-Osorio, et. al. 2008; Ferreira 2009).

effects model with time varying family effects to study sibling peer effects in risky behaviors such as smoking, drinking and drug use in the 79 NLSY. They assume that initially, an older sibling can influence a younger sibling but not vice versa for identification. They find evidence for weak sibling peer effects for risky behaviors. Kuziemko 2006 studied sibling peer effect on the timing of fertility using data from both the Panel Study of Income Dynamics and NLSY. She found that a woman is more likely to have a child within two years of her sister having a child.

1 The Framework

Consider an independent sample of families, $h = 1, .., H$. Each family has two siblings, $i = 1, 2$.

All data are demeaned by birth order and gender.

Let y_{ih} be the dependent variable of sibling i in household h. In this paper, y_{ih} may be log(height), log(weight), or log(BMI).

Let g_{ih} be the gender of sibling i in household h. $g_{ih} = \{m, f\}$ where m is a male and f is a female.

Let Q_{ih} be a $K \times 1$ vector of own covariates with the property that $E(Q_{ih} - Q_{-ih})(Q_{ih} - Q_{-ih})'$ is positive definite.

Subpressing the h subscript, the outcome equation for sibling i in household h is:

$$y_i = \pi_{g_i} y_{-i} + Q_i' \widetilde{\beta}_{g_i} + Q_{-i}' \gamma_{g_i} + v_i \qquad i = 1, 2 \tag{1}$$

$$v_i \not\perp Q_i, Q_{-i} \tag{2}$$

where v_i is an error term of the outcome equation. Because v_i contains left out variables, including unobservable factors that are common to both siblings, v_i is not assumed to be orthogonal to Q_i or Q_{-i}.

π_{g_i}, the sibling interaction effect, is allowed to be gender specific. In some settings, even a gender pair specific sibling interaction effect, $\pi_{g_i g_{-i}}$, is identified. We stick with the simpler formulation because, in our empirical work, we are unable to precisely estimate the parameters of the more general model.

Note that $i's$ sibling's covariates, Q_{-i}, are allowed to directly influence y_i.

The above model can be written in Manski's linear in mean peer effects model form,

$$y_i = \pi_{g_i} y_{-i} + Q_i' \beta_{g_i} + [Q_i + Q_{-i}]' \gamma_{g_i} + v_i \tag{3}$$

$$\beta_{g_i} = \widetilde{\beta}_{g_i} - \gamma_{g_i}$$

There are two important special cases of our interaction model (3).

First, there is the influential sibling difference model:

$$y_i = Q_i' \widetilde{\beta}_{g_i} + v_i \qquad i = 1, 2 \tag{4}$$

and assumption SD1:

$$E(Q_i - Q_{-i})(v_i - v_{-i}) = 0 \tag{5}$$

Assumption SD1, which is untested, says that family differences in covariates are orthogonal to family differences in error terms in equation (4).

Also, π_{g_i} and γ_{g_i} are assumed to be zero. That is, there is no sibling interaction effect or contextual effect in the sibling difference model. In most empirical applications, these exclusion restrictions are also untested.

We will build on the sibling difference model by strengthening assumption SD1. In return, we can identify π_{g_i} as well as test whether $\pi_{g_i} = 0$ and $\gamma_{g_i} = 0$.

Before proceeding, it is useful to clarify what we identify if we run the usual difference regression in the presence of peer and contextual effects. Restrict attention to same-sex sibling households, i.e. those with $g_1 = g_2$. Differencing (3) yields

$$\begin{aligned} y_1 - y_2 = {} & \pi_{g_1}(y_2 - y_1) \\ & + (Q_1 - Q_2)' \beta_{g_1} + \nu_1 - \nu_2 \end{aligned} \tag{6}$$

Therefore, we can write the difference as

$$\Delta y = (Q_1 - Q_2)' \frac{\beta_{g_1}}{1 + \pi_{g_1}} + \frac{(\nu_1 - \nu_2)}{1 + \pi_{g_1}} \quad g_1 = g_2 \in \{m, f\} \tag{7}$$

Under assumption SD1 (implied by A1) and our requirement that the covariance matrix of $(Q_i - Q_{-i})$ is positive definite, which are the standard assumptions used in the sibling difference literature, we can identify

$$\frac{\beta_m}{1 + \pi_m} \quad \text{and} \quad \frac{\beta_f}{1 + \pi_f} \tag{8}$$

So, we can treat these parameters as known when addressing the identification of the peer effects. Define $\widetilde{Q_i} = Q_i' \beta_{g_i} / \left(1 + \pi_{g_i}\right)$. Substituting back into (3), we obtain

$$\begin{aligned} & y_i = \pi_{g_i} y_{-i} + \left(1 + \pi_{g_i}\right) \widetilde{Q_i} + [Q_i + Q_{-i}]' \gamma_{g_i} + v_i \\ \Leftrightarrow\ & y_i - \widetilde{Q_i} = \pi_{g_i} \left(y_{-i} + \widetilde{Q_i}\right) + [Q_i + Q_{-i}]' \gamma_{g_i} + v_i \end{aligned} \tag{9}$$

For the purpose of studying identification, if we are willing to maintain SD1 we can act as if our interest is the estimation of (9), where the variable $\widetilde{Q_i}$ is observed. Our approach is to suggest an IV estimator that is orthogonal to $[Q_i + Q_{-i}]' \gamma_{g_i} + v_i$ but correlated with $\left(y_{-i} + \widetilde{Q_i}\right)$.

A second special case of our model occurs when there is no heterogeneity. Manski's original model assumes that the parameters in (3) are not gender specific. Also Q_i and Q_{-i} are independently and identically drawn from the same multivariate distribution. Thus there is no parametric difference in the determinants of outcomes or covariates for different members of a peer group. As we will show below, our identification strategy fails, as is well known from Manski's original work, under his homogeneity postulate. However, we believe that when the peer group is a sibling group of mixed gender, this homogeneity assumption is too strong. Our identification strategy depends on heterogeneity in the determinants of outcomes or covariates by gender. Importantly, the presence of this heterogeneity is testable.

We now state our assumptions:

Assumptions

$$E((Q_i - Q_{-i})v_i) = 0 \qquad i = 1,2 \tag{A1}$$

$$E((Q_i - Q_{-i})(Q_i + Q_{-i})'\gamma_{g_i}) = 0 \qquad i = 1,2 \tag{A2}$$

$$E((Q_i - Q_{-i})(Q_i \frac{\beta_{g_i}}{1+\pi_{g_i}} + Q_{-i} \frac{\beta_{g_{-i}}}{1+\pi_{g_{-i}}}) \neq 0 \tag{A3}$$

A1 strenghtens assumption SD1. It says that the difference in covariates is orthogonal to the level of the error in equation (3). A1 implies SD1 but not vice versa. Like assumption SD1 in the sibling difference model, we maintain A1.

A2 is satisfied if Q_i and Q_{-i} are exchangeable, which is sufficient to generate the required "symmetry" property $E(Q_i - Q_{-i})(Q_i + Q_{-i})' = 0$. This symmetry property is testable. If exchangeability is not satisfied, A2 is also satisfied if there is no contextual effect, i.e. $\gamma_{g_i} = 0$.

A3 says that the standardized parameters of own covariates which determine outcomes differ by gender. This is a testable assumption. Generically, A3 can be satisfied if $E(Q_i - Q_{-i})(Q_i + Q_{-i})' \neq 0$ and/or $\beta_{g_i} \neq \beta_{g_{-i}}$ and/or $\pi_{g_i} \neq \pi_{g_{-i}}$.[14]

For notational simplicity, we have written the assumptions in terms of the differences of all the covariates. But it should be clear, from our discussion of what can be identified from the sibling difference regression, that we can replace $(Q_i - Q_{-i})$ with any known nontrivial linear combination $c'(Q_i - Q_{-i})$ in A1-A3.

We can motivate A1 and A2 in two ways.

Under the first set of assumptions, **A,** the covariates satisfy certain symmetry restrictions:

Aa. $f(v_i|Q_i, Q_{-i})$ is exchangeable in Q_i, Q_{-i} (Altonji and Matzkin 2005):

$$v_i = \lambda_{g_i}(Q_i + Q_{-i}) + \omega_i; \ \omega_i \perp Q_i, Q_{-i}$$

Ab: Q_i and Q_{-i} are exchangeable:

$$E(Q_i - Q_{-i})(Q_i + Q_{-i})' = 0$$

[14] Let the observable difference between siblings be birth order. Following Altonji, et. al. 2010, assume that the older sibling's behavior affects the younger sibling and not vice versa. Then A2 is generically satisfied since the interaction effects of the two siblings are different.

Aa says that the projection of v_i on Q_i and Q_{-i} is the same as the projection onto their sum. Aa and Ab impy A1 and A2. Aa implies assumption SD1 of the sibling difference model.

If **A** applies, contextual effects may be present but only the sum $\gamma_{g_i} + \lambda_{g_i}$ of its effects on outcomes can be estimated.

Alternatively under a second set of assumptions, **B**, the covariates have a factor structure and there is no contextual effect:

$$\begin{aligned} Q_i &= \phi F + w_i;\ F \perp w_i, w_{-i} \\ v_i &= \eta_{g_i} h + \varepsilon_i;\ \varepsilon_i \perp h, w_i, w_{-i} \\ \gamma_{g_i} &= 0;\ i = 1, 2 \end{aligned}$$

B also implies A1 and A2. It also implies assumption SD1 of the sibling difference model.

A and **B** are closely related, but neither implies the other.

In **A,** exchangeability of Q_i and Q_{-i} implies that $E(Q_i - Q_{-i})Q_i' = E(Q_{-i} - Q_i)Q_{-i}'$. Then A3 has to be satisfied by $\beta_{g_i} \neq \beta_{g_{-i}}$ and/or $\pi_{g_i} \neq \pi_{g_{-i}}$. A2 automatically holds.

In **B,** A3 may also be satisified by $E(Q_i - Q_{-i})Q_i' \neq E(Q_{-i} - Q_i)Q_{-i}'$. But if we relax Ab, we must rule out the presence of contextual effects to obtain A2.

We now have the following theorem:

Theorem 1

1. Assume A1, A2 & A3. Then π_{g_i} in equation (3) is identified.

2. Under A1, the sibling difference model

$$\begin{aligned} y_i &= Q_i' \widetilde{\beta}_{g_i} + v_i \qquad i = 1, 2 \\ \pi_{g_i} &= 0 \text{ and } \gamma_{g_i} = 0 \end{aligned} \tag{10}$$

   is testable.

Proof: See appendix

The theorem says that gender specific interaction effects are identified.

If $K \geq 2$, the theorem can be extended to identify gender pair specific interaction effects, $\pi_{g_i g_{-i}}$. We can also allow for intercepts by birth order.

In order to provide intuition as to how we get identification of interaction effects relative to Manski's original linear in means peer effects model, note that A3 introduces more parameters than in his model. His formulation:

$$E(Q_i - Q_{-i})Q_i' = E(Q_{-i} - Q_i)Q_{-i}';\ \ \beta_{g_i} = \beta;\ \pi_{g_i} = \pi;$$

violates A3.

When $g_i \neq g_{-i}$, his model implies for brothers (m) and sisters (f):

$$cov(y_m, y_m) = cov(y_f, y_f)$$
$$Cov(y_m, Q_m) = Cov(y_f, Q_f)$$
$$Cov(y_m, Q_f) = Cov(y_f, Q_m)$$

Under our assumption A3,

$$cov(y_m, y_m) \neq cov(y_f, y_f) \tag{11}$$
$$Cov(y_m, Q_m) \neq Cov(y_f, Q_f) \tag{12}$$
$$Cov(y_m, Q_f) \neq Cov(y_f, Q_m) \tag{13}$$

which gives us significantly more distinct observable moments relative to the additional parameters.

2 Testing the sibling difference model

Assume A1.

Step 1. Use the sample of sisters, (f, f), to take sibling differences of equation (3). Then estimate the resulting differenced equation by OLS to get an estimate of β^{SD}:

$$y_i - y_{-i} = [Q_i - Q_{-i}]'\beta_f^{SD} + \frac{v_i - v_{-i}}{1 + \pi_f} \tag{14}$$
$$\beta_f^{SD} = \beta_f (1 + \pi_f)^{-1}$$

$\widehat{\beta}_f^{SD}$ is a consistent estimate of $\beta_f (1 + \pi_f)^{-1}$.

Step 2. Consider the sample of girls in mixed gender, (f, m), siblings. Using equation (3), estimate γ_f in

$$y_f - Q_f'\beta_f^{SD} = Z_f \gamma_f + w_f \tag{15}$$
$$w_f = \pi_f y_{-f} + Q_f' \left(\beta_f - \beta_f^{SD} \right) + [Q_i + Q_{-i}]'\gamma_f + v_f$$
$$= \pi_f \left(y_{-f} + Q_f'\beta_f^{SD} \right) + [Q_i + Q_{-i}]'\gamma_f + v_f$$

using $[Q_m - Q_f]$ as instrumental variable candidates for Z_f. If the sibling difference model is correct, then we should have $\gamma_f = 0$ for any choice of Z_f which provides the basis for a useful specification test. Interesting choices for Z_f include (i) $Z_f = Q_m - Q_f$,(ii) $Z_f = y_{-f} + Q_f'\beta_f^{SD}$, and (iii) $Z_f = Q_f$. Choosing $Z_f = Q_m - Q_f$ seems natural to test $E(Q_m - Q_f)\left(y_f - Q_f'\beta_f^{SD} \right) = 0$, as we would expect if the sibling difference specification was correct, along with A1.

Choosing $Z_f = y_{-f} + Q_f' \beta_f^{SD}$ provides a one-dimensional test of the siblling difference model, which may have more power than the K-dimensional test in (i). Moreover, under A1-A3, γ_f estimates π_f. However, implementing the specification test is complicated by the fact that in practice we would replace $y_f - Q_f' \beta_f^{SD}$ with $y_f - Q_f' \widehat{\beta}_f^{SD}$, so we must take into account the parameter uncertainty in $\widehat{\beta}_f^{SD}$ when making inferences about γ. We describe how to do this in the next session for the case $Z_f = y_{-f} + Q_f' \beta_f^{SD}$. But the choice $Z_f = Q_f$ leads to an important simplification which makes it particularly well-suited as a specification test.

Conside estimation of the β_f^{IV} in

$$
\begin{aligned}
y_f &= Q_f' \beta_f^{IV} + \widetilde{w}_f \\
\widetilde{w}_f &= \pi_f y_{-f} + [Q_i + Q_{-i}]' \gamma_f + v_f
\end{aligned}
$$

using $[Q_m - Q_f]$ as instruments for Q_f. $Q_f \gamma_f = 0$ in (3) iff $\beta_f^{IV} = \beta_f^{SD}$. But, as $\widehat{\beta}_f^{IV}$ and $\widehat{\beta}_f^{SD}$ are constructed from independent samples, using $\widehat{\beta}_f^{IV} - \widehat{\beta}_f^{SD}$ to test $\beta_f^{SD} = \beta_f^{IV}$ is straightforward. Part B of the appendix evaluates $(\beta_f^{IV} - \beta_f^{SD})$ in the presence of peer and contextual effects and shows that it is generically nonzero.

Under **A,** $\widehat{\beta}_f^{IV}$ is a consistent estimator for β_f as long as $\pi_f = 0$ (no peer effect).

Under **B,** $\widehat{\beta}_f^{IV}$ is a consistent estimator for β_f as long as $\pi_f = 0$, and $\gamma_{g_i} = 0$ (no contextual effect).

Under **A**, if $\pi_f = 0$, then

$$
p \lim \beta_f^{IV} = p \lim \beta_f^{SD} = \beta_f
$$

So if **A** is valid and we reject $H_0 : \beta_f^{IV} = \beta_f^{SD}$, we will have rejected the hypothesis that $\pi_f = 0$. The test sheds no light on the presence of contextual effects.

Similarly, If **B** valid and we reject $H_0 : \beta_f^{IV} = \beta_f^{SD}$, we will have rejected the joint hypothesis that $\pi_f = 0$ and $\gamma_f = 0$.

We can repeat step 1 for the sample of brothers and step 2 for the sample of boys in mixed gender siblings to test for the corresponding sibling difference model for boys.

3 Estimating π_f

We first provide a two step estimator that is easy to understand and follows closely our constructive approach to identification.

Step 1: Use the sample of sisters, (f, f), to estimate $\beta_f^{SD} = \beta_f(1+\pi_f)^{-1}$ by OLS as was done above.

Step 2: Using equation (3) and treating β_f^{SD} as given, estimate π_f with sisters from mixed gender, (f, m), sample:

$$y_f - Q_f'\beta_f^{SD} = \pi_f \left[y_m + Q_f'\beta_f^{SD}\right] + \omega_f \tag{16}$$

$$\omega_f = [Q_f + Q_m]'\gamma_f + v_f \tag{17}$$

by plugging in our estimate of $\widehat{\beta}_f^{SD}$ for β_f^{SD} in equation (16) and using $[Q_m - Q_f]$ as an instrument for $\left[y_m + Q_f'\widehat{\beta}_f^{SD}\right]$.

Assumption A1&A2 implies that ω_f is orthogonal to our instrument even though contextual effects, $\gamma_f \neq 0$, are potentially present.

In the two step estimator, we plug in $\widehat{\beta}_f^{SD}$ for our second step. This makes the two step estimator inefficient relative estimating equations (14) and (16) simultaneously by GMM.

We can also include a third step and estimate $\gamma_f + \lambda_f$, which may be of interest, by running the OLS regression

$$y_f - \pi_f y_m - (1+\pi_f)Q_f'\beta_f^{SD} = [Q_f + Q_m]'\left(\gamma_f + \lambda_f\right) + \widetilde{\omega}_f$$

and plugging in the estimated values from Step 1 and Step 2 for the unknown parameters on the left hand side of the equality.

4 Data

We use two datasets for our empirical work. One is the 1978 National Longitudinal Study of Youths (NLSY). The second dataset consists of the children of the women in the NLSY (CNLSY).

We will discuss the CNLSY sample first. An observation is a sibling pair consisting of two contiguously aged siblings. In order to maximize the number of observations, if there are more than two siblings in the dataset, middle siblings were counted twice, once as the younger sibling of an older sibling, and once as the older sibling with a younger sibling. We ignored the within family correlation across observations. We deleted outliers by birth weight, weight and height in 1990, shrinkage in height, and individuals younger than age 2 in 1990. We ended up with 1810 sibling pairs.

Table 1 shows that the average age of the older and younger sibling was 9.4 and 6.4 respectively. 0.505 older siblings and 0.519 younger siblings were male. We do not reject the hypothesis that there is no sex ratio difference by birth order at the 1% significance leve. The average birth weight of older and younger siblings were 115 and 117 ounces respectively. The difference in average height and weight between older and younger siblings was 7 inches and 378 ounces respectively. The difference in average BMI by birth order was 0.8 kg/m^2. The hypotheses of no difference in average height, weight and BMI by birth order are each rejected at the 5% significance level.

The correlations in birth weight, weight, height and BMI in 1990 between siblings were 0.40, 0.68, 0.73 and 0.37 respectively.

5 Empirical results

In all regressions, all variables were demeaned by birth order and gender. For each covariate, q_{gi}, in the mixed gender siblings sample, we regress $(q_m + q_f)$ on $(Q_m - Q_f)$. We always rejected the hypothesis of exchangeability of Q_m and Q_f for all the covariates.[15] Thus our sibling difference tests and estimation results proceeded under the set of assumptions **B** which excluded contextual effects.

Table 2 presents estimates where the dependent variable is the log of height in inches. The height of a child is of course affected by his or her age. Another well known determinant of a child's health is his or her birth weight.[16] Column 1 presents estimates of the sibling difference in log height (ΔLHT_g) on sibling differences in age (ΔAGE_g), log of birth weight (ΔLBW_g) and ($\Delta(AGE_g \times LBW_g)$) for same gender siblings, $g_i = m, f$. For both genders, there were 797 observations which means that the gender specific coefficients were estimated using approximately 400 observations each. For brothers, the coefficients on ΔAGE_g and $\Delta(AGE_g \times LBW_g)$ are precisely estimated. For sisters, all three coefficients are precisely estimated. The test for the equality of the male and female coefficients, $\widetilde{\beta}_f = \widetilde{\beta}_m$, has a p-value of 0.02. Thus our test of the sibling difference model and IV estimate of the sibling interaction effects will have power.

Using the sample of mixed gender siblings of 811 observations, Column (2) provides IV estimates of the effects of AGE_m, LBW_m and $AGE_m \times LBW_m$ on LHT_m where the instruments were ΔQ_i. Using the Kleibergen-Paap rank test, the test of Assumption A3 has a p-value smaller than 0.001. All three coefficients were estimated precisely. The point estimates of the coefficients from the IV regression is quantitatively similar to that from the sibling difference regression. The test of equality of the boys' coefficients between column (1) and (2) has a p-value of 0.65. So there is no evidence against the sibling difference model. Since we do not expect a sibling interaction effect on height, this finding is reassuring.

Column (4) presents IV estimates of the effects of AGE_f, LBW_f and $AGE_f \times LBW_f$ on LHT_f where the instruments were ΔQ_g. Again, using the Kleibergen-Paap rank test, the test of Assumption A3 has a p-value smaller than 0.001. All three coefficients were estimated precisely. The point estimates of the coefficients from the IV regression is quantitatively similar to that from the sibling difference regression. The test of equality of the girls' coefficients between col-

[15]We did not reject this hypothesis for some covariates in some tables.

[16]See Black 2007 and the references therein.

umn (1) and (4) has a p-value of 0.54. So again there is no evidence against the sibling difference model.

We summarize the results of the tests of the SD model for height. For both boys and girls, the estimates of the coefficients of the own effects were largely precisely estimated in columns (1), (2) and (4). Based on the Kleibergen-Paap rank test for the IV regressions, there is no evidence against Assumption A3. Thus the lack of evidence against the SD model for brothers and sisters is not due to lack of power. Rather, it strongly suggests that there is no sibling interaction effect in the determination of height. Moreover, since exchangeability of Q_{g_i} fail, being unable to reject the SD model also implies that there is no contextual effect in the determination of height.

In columns (3) and (5), we use the two step estimator IV to estimate the sibling interaction effects, π_m and π_f, respectively. We did not correct the standard errors for using a constructed regressor in the second stage. Thus the reported standard errors for the interaction effects are underestimates of the true standard errors. The point estimate for π_m was -0.010 with a standard error of 0.052. The point estimate of π_f was -0.022 with a standard error of 0.057. Both point estimates are quantitatively small and given the downward biased standard errors, we certaintly cannot reject the hypothesis that there is no sibling interaction effect in height for both brothers and sisters.

In column (6), we use a two step GMM estimator to estimate π_m and π_f.[17] Under GMM, the sibling difference regressions and the IV regressions are estimated simultaneously with non-linear cross equations restrictions. The GMM estimates for π_m and π_f are -0.13 with a standard error of 0.004 and 0.044 with a standard error of 0.006. The negative point estimate for π_m and its associated small standard error is behaviorally implausible. The point estimate for π_f is 0.04 and is statistically different from zero at the 0.01 significance level. Comparing the results from the SD tests, the two step IV estimates for π_m and π_f, the behavioral implausibility of sibling interaction effects in the determination of height, it is likely that the GMM estimator has poor properties given our small sample size.[18]

Based on our analysis of the determination of height, we tentatively conclude that our testing and estimation strategy for sibling interaction effects has power. The two step IV estimator is more robust than than the GMM estimator given our small sample size. Both the SD test and two step IV estimator suggest that there is no sibling interaction effect in height.

Table 3 presents estimates where the dependent variable is the log of weight in 1990. In addition to age, we use height as a determinant of weight, consistent with the use of BMI, which weight corrected for height, in the medical literature. We relax the implicit BMI restriction which says that the coefficient of log height on log weight is 2. Column 1 presents OLS estimates of the sibling difference in log weight (ΔLWT_g) in 1990 on sibling differences in age (ΔAGE_g),

[17]The first step is used to construct a consistent estimate of the variance covariance matrix which is used to construct the GMM estimator in the second step.

[18]We experimented with other system estimators and obtained different point estimates. These diversity of estimates raises more doubt about system estimation with our sample size.

log of height in 1990 (ΔLHT_g) and ($\Delta(AGE_g \times LHT_g)$) for same gender siblings, $g = m, f$. For both genders together, there were 876 observations. For brothers as well as sisters, all coefficients were precisely estimated. The test for the equality of the male and female coefficients, $\widetilde{\beta}_f = \widetilde{\beta}_m$, has a p-value of 0.78. That is, we cannot reject the hypothesis that $\widetilde{\beta}_f = \widetilde{\beta}_m$ which raises the questions as to how powerful is our test of the sibling difference model and whether we will obtain precise estimates of the sibling interaction effects.

Using the sample of mixed gender siblings of 890 observations, Column (2) provides IV estimates of the effects of AGE_m, LHT_m and $AGE_m \times LHT_m$ on LWT_m where the instruments were ΔQ_i. Using the Kleibergen-Paap rank test, the test of Assumption A3 has a p-value smaller than 0.001. Since we do not reject the hypothesis that $\widetilde{\beta}_f = \widetilde{\beta}_m$, Assumption A3 can hold only if

$$E(Q_f - Q_m)(Q_f + Q_m) \neq 0$$

which means we have to reject exchangeability of Q_f and Q_m. As discussed earlier, we always rejected the hypothesis of exchangeability of Q_m and Q_f for all the covariates. Thus there should be no concern about weak instruments.

All three coefficients in column (2) were estimated precisely. The point estimates of the coefficients from the IV regression is quantitatively similar to that from the sibling difference regression. The test of equality of the boys' coefficients between column (1) and (2) has a p-value of 0.68. Since all the coefficents in both columns (1) and (2) were estimated precisely, the lack of evidence against the SD model is not due to lack of power. This is very strong evidence that there is little or no sibling interaction effect on weight among boys.

Column (3) presents our two step IV estimate of π_m. The point estimate of π_m is -0.077 with a standard error of 0.029. As discussed above, the precision of the estimate is a lower bound.

Column (4) presents IV estimates of the effects of AGE_f, LHT_f and $AGE_f \times LHT_f$ on LWT_f where the instruments were ΔQ_g. Again, using the Kleibergen-Paap rank test, the test of Assumption A3 has a p-value smaller than 0.001. All coefficients were again estimated precisely. The point estimates of all the coefficients from the IV regression were quantitatively similar to that from the sibling difference regression. The test of equality of the girls' coefficients between column (1) and (4) has a p-value of 0.59. All the estimates of the coefficients in both columns (1) and (4) were precisely estimated. Thus again, the lack of evidence against the SD model for sisters is not due to lack of power.

Column (5) presents the two step IV estimate of π_f. The point estimate for π_f was 0.008 with a standard error of 0.039. The point estimate for π_f is small. We cannot reject the hypothesis that it is zero although a small positive estimate cannot be rejected.

Column (6) presents GMM estimates of the entire model. All the parameters of the model were estimated precisely. The estimate for π_m was -0.059 with a small standard error. Since we do not reject the SD model, the estimate for π_m suggests a small negative interaction effect for brothers toward their sibling's weight. Negative sibling interaction effect in weight cannot be ruled out apriori. One sibling may react against the other sibling being too heavy or too thin. Another mechanism is that the two siblings compete for food within the family.

The point estimate of π_f was 0.02 also with a small standard error. In this case, our non rejection of the SD model for girls and the precisely estimated small positive estimate for π_f suggests that sisters are positively influenced by their siblings' weight.

We summarize the results in Table 3. We obtain precise estimates of almost all coefficients for all the estimated models. We cannot reject the hypothesis that $\widetilde{\beta}_f = \widetilde{\beta}_m$ which implies that when the IV regressions do not suffer from a weak instrument problem, exchangeablitity of Q_m and Q_f is rejected. Since we also cannot reject the SD model, the sibling interaction effects are either zero or quantitatively small. Our point estimates of π_m and π_f are in fact quantitatively small. Interestingly enough, the estimate of π_m is negative whereas that for π_f is positive. Thus there is some evidence that boys react differently than girls toward their siblings weight gain. Finally the difference in signs for the estimates of the sibling interaction effect by gender supports the validity of Assumption A3.

Table 4 presents estimates where the dependent variable is the log of BMI. If the previous model on the determination of weight is correct, the implicit restriction of BMI that the log of weight is twice the log of height already generates model misspecification. Since BMI is standard dependant variable in the literature on the determinants of obesity, we also investigate its determinants here.

Column 1 presents estimates of the sibling difference in log BMI (ΔLHT_g) in 1990 on sibling differences in age (ΔAGE_g), log of birth weight (ΔLBW_g) and ($\Delta(AGE_g \times LBW_g)$) for same gender siblings, $g = m, f$. For both genders, there were 797 observations. For brothers, the coefficient on ΔAGE_g is precisely estimated. For sisters, the coefficients on ΔAGE_g) and ΔLBW_g are precisely estimated. The test for the equality of the male and female coefficients, $\widetilde{\beta}_f = \widetilde{\beta}_m$, has a p-value of 0.26. Thus we cannot reject the hypothesis that $\widetilde{\beta}_f = \widetilde{\beta}_m$. This is not different from our investigation in Table 3 using LWT_g as a dependent variable although some covariates are different. On the other hand, since $\widetilde{\beta}_f$ and $\widetilde{\beta}_m$ are not all estimated precisely in column (1), there is a question on the power of the test.

Using the sample of mixed gender siblings of 811 observations, Column (2) provides IV estimates of the effects of AGE_m, LBW_m and $AGE_m \times LBW_m$ on $LBMI_m$ where the instruments were ΔQ_i. Using the Kleibergen-Paap rank test, the test of Assumption A3 has a p-value smaller than 0.001. The coefficients on AGE_m and LBW_m were estimated precisely. The point estimates of the coefficients from the IV regression is quantitatively similar to that from the sibling difference regression. The test of equality of the boys' coefficients between column (1) and (2) has a p-value of 0.69. While there is no evidence against the sibling difference model, since the point estimates of the boys' coefficients are rather imprecise, and only two coefficients in column (2) were estimated precisely, it is possible that the inability to reject the SD model for boys is due to a lack of power.

Column (3) presents our two step IV estimate of π_m. The point estimate of π_m is -0.087 with a standard error of 0.032. The precision of the point estimate is implausible given that we cannot reject the SD model and also the imprecision of the estimates in columns (1) and (2). Moreover the relatively large negative point estimate of π_m is behaviorally suspect. We tentatively conclude that there may be evidence consistent with a small negative sibling interaction effect for boys.

Column (4) presents IV estimates of the effects of AGE_f, LBW_f and $AGE_f \times LBW_f$ on $LBMI_f$ where the instruments were ΔQ_g. Again, using the Kleibergen-Paap rank test, the test of Assumption A3 has a p-value smaller than 0.001. The coefficients on AGE_m and LBW_m were estimated precisely. The point estimates of the coefficients on AGE_m and LBW_m from the IV regression is quantitatively similar to that from the sibling difference regression. The test of equality of the girls' coefficients between column (1) and (4) has a p-value of 0.97. The estimates of the coefficients on AGE_m and LBW_m in both columns (1) and (4) were precisely estimated. Thus the lack of evidence against the SD model for sisters is not due to lack of power.

Column (5) presents the two step IV estimate of π_f. The point estimate for π_f was 0.049 with a standard error of 0.048. The point estimate for π_f is small. We cannot reject the hypothesis that it is zero. However the relatively large standard cannot preclude a positive interaction effect.

Column (6) presents GMM estimates of the entire model. All the parameters of the model were estimated precisely. The estimate for π_m was -0.097 with a small standard error. The point estimate of π_f was 0.12 again with a small standard error. The precision of the estimates by GMM is somewhat implausible given the single equation results in columns (1), (2) and (4), and the lack of evidence against the SD model for both brothers and sisters.

We summarize our results from Table 4 on BMI as follows. Due to the small sample size and the potential for model misspecification of the BMI model due to its restriction on the interaction between weight and height, the estimates from the sibling difference regression and the IV regression are imprecise. Moroever our inability to reject of $\widetilde{\beta}_f = \widetilde{\beta}_m$ raises the question of power in our testing and estimation procedure. We do not reject the SD model for both brothers and sisters, perhaps partly due to lack of power. Taken at face value, the point estimates for π_m and π_f in Table 4 suggest that brothers react negatively to their sibling's BMI whereas sisters react positively to their sibling's BMI.

The results from Tables 2, 3 and 4 suggest that to a first order, sibling interaction effects in weight are either zero or quantitatively small. More interestingly, the estimated interaction effects are qualitatively different. Brothers react negatively to their siblings weight gain whereas sisters react positively. Due to our small sample, these conclusions are provisional. In particular, the small sample properties of GMM may be an issue.

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Appendix

A. Proof of Theorem 1: In what follows, we rule out a priori degenerate cases for the peer effect parameters $(\pi_m = -1, \pi_f = -1, \pi_m\pi_f = 1)$,.

For mixed-sex sibling households, it is convenient to rewrite the model given by eq(3) explicitly in terms of the data for the male and female sibling

$$\begin{aligned} y_m &= \pi_m y_f + Q_m'\beta_m + (Q_m + Q_f)'\gamma_m + \nu_m \\ y_f &= \pi_f y_f + Q_f'\beta_f + (Q_m + Q_f)'\gamma_f + \nu_f \end{aligned} \tag{18}$$

Solving the two equations for y_m and y_f yields

$$\begin{aligned} y_m &= \frac{1}{\Delta}\left(Q_m'\beta_m + \pi_m Q_f'\beta_f + (Q_m + Q_f)'\left(\gamma_m + \pi_m\gamma_f\right) + \nu_m + \pi_m\nu_f\right) \\ y_f &= \frac{1}{\Delta}\left(Q_f'\beta_f + \pi_f Q_m'\beta_m + (Q_m + Q_f)'\left(\gamma_f + \pi_f\gamma_m\right) + \nu_f + \pi_f\nu_m\right) \end{aligned} \tag{19}$$

where $\Delta = 1 - \pi_m\pi_f$.

To demonstrate the identification of the peer effect parameters, first focus on the equation for males in the mixed-sex sibling household. Define $\widetilde{Q}_m = Q_m'\beta_m/(1+\pi_m)$. We can rewrite the model for males from eq(18) as

$$\begin{aligned} y_m &= \pi_m y_f + (1+\pi_m)\widetilde{Q}_m + (Q_m + Q_f)'\gamma_m + \nu_m \\ &\Leftrightarrow y_m - \widetilde{Q}_m = \pi_m\left(y_f + \widetilde{Q}_m\right) + (Q_m + Q_f)'\gamma_m + \nu_m \end{aligned} \tag{20}$$

Assumptions *A1* and *A2* imply

$$\begin{aligned} E(Q_m - Q_f)\nu_m &= E(Q_m - Q_f)\nu_f = 0 \\ E(Q_m - Q_f)(Q_m + Q_g)'\gamma_m &= E(Q_m - Q_f)(Q_m + Q_f)'\gamma_f = 0 \end{aligned} \tag{21}$$

Premultiplying eq(20) by $Q_m - Q_f$ and taking expectations, the identification/rank condition for π_m is

$$rank\left(E(Q_m - Q_f)\left(y_f \;+\; \widetilde{Q}_m\right)\right) = 1 \tag{22}$$

But

$$E(Q_m - Q_f)\left(y_f \ + \ \widetilde{Q}_m\right) \tag{23}$$
$$= E(Q_m - Q_f)\left(\frac{Q_f'\beta_f + \pi_f Q_m'\beta_m}{1-\pi_m\pi_f} + \frac{Q_m'\beta_m}{1+\pi_m}\right)$$
$$= E(Q_m - Q_f)\left(Q_f{}'\frac{\beta_f}{1-\pi_m\pi_f} + Q_m'\left(\frac{\pi_f\beta_m}{1-\pi_m\pi_f} + \frac{\beta_m}{1+\pi_m}\right)\right)$$
$$= E(Q_m - Q_f)\left(Q_f{}'\frac{\beta_f}{1-\pi_m\pi_f} + Q_m'\left(\frac{\left(1+\pi_f\right)\beta_m}{\left(1-\pi_m\pi_f\right)(1+\pi_m)}\right)\right)$$
$$= \frac{\left(1+\pi_f\right)}{\left(1-\pi_m\pi_f\right)}E(Q_m - Q_f)\left(Q_f{}'\frac{\beta_f}{1+\pi_f} + Q_b'\frac{\beta_m}{1+\pi_m}\right)$$

By the same line of argument, the identification condition for π_g is

$$\frac{(1+\pi_m)}{\left(1-\pi_m\pi_f\right)}E(Q_m - Q_f)\left(Q_f{}'\frac{\beta_f}{1+\pi_f} + Q_m'\frac{\beta_m}{1+\pi_m}\right) \neq 0 \tag{24}$$

As we've ruled out degenerate cases for (π_m, π_f), we see that the same condition guarantees identification of both peer effect coefficients.

A necessary condition for identification of the peer effect parameters is

$$\frac{\beta_m}{1+\pi_m} \neq 0 \ \text{ or } \frac{\beta_f}{1+\pi_f} \neq 0 \tag{25}$$

If condition Ab holds, then $\frac{\beta_m}{1+\pi_m} \neq \frac{\beta_f}{1+\pi_f}$ is necessary and sufficient. Notice that even if $\frac{\beta_m}{1+\pi_m} = \frac{\beta_f}{1+\pi_f} \neq 0$, so there is no heterogeneity in the sibling difference regression coefficients across gender, we can still identify the peer effects provided there is enough heterogeneity in the covariate distribution such that $E(Q_m - Q_f)\left(Q_f + Q_m\right)' \neq 0$.

B. Evaluating $\beta_m^{IV} - \beta_m^{SD}$

If the sibling difference model eq(10) is correct, then assumption *A1* implies that for males from mixed sibling households

$$E(Q_m - Q_f)\left(y_m \ - \ Q_m'\beta_m^{SD}\right) = E(Q_m - Q_f)Q_m'\left(\beta_m^{IV} - \beta_m^{SD}\right) = 0 \tag{26}$$

which just says that the difference in sibling covariates should be orthogonal to the "level" disturbance. The relationship in (26) is easily estimated. But, using the results above, we can evaluate the left hand side of (26) in the presence of peer and contextual effects. For mixed sibling households,

$$
\begin{aligned}
E(Q_m - Q_f)\left(y_m \;-\; Q_m'\beta_m^{SD}\right) &= E(Q_m - Q_f)\left(y_m \;-\; \widetilde{Q}_m\right) \\
&= E(Q_m - Q_f)\left(\pi_m\left(y_f + \widetilde{Q}_m\right) + (Q_m + Q_f)'\gamma_m\right) \text{ by (20)} \\
&= \frac{\pi_m\left(1+\pi_f\right)}{\left(1-\pi_m\pi_f\right)} E(Q_m - Q_f)\left(Q_f{}'\frac{\beta_f}{1+\pi_f} + Q_m'\frac{\beta_m}{1+\pi_m}\right) \\
&+ \frac{1}{\left(1-\pi_m\pi_f\right)} E(Q_m - Q_f)(Q_m + Q_f)'(\gamma_m + \pi_m\gamma_f)
\end{aligned}
$$

A nonzero value for the right hand side would allow us to reject the sibling difference model under the maintained assumption *A1*. So $\pi_m \neq 0$ and the identification condition *A3*, or violation of *A2* are generically sufficient to allow us to test the sibling difference regression model.

The value of $E(Q_m - Q_f)\left(y_f \;-\; \widetilde{Q}_f\right)$ can be obtained using the same reasoning and looks similar–just switch all the m and f subscripts.

Table 1: CNLSY 1990 (1810 sibling pairs)

	Mean	Std Deviation	Min	Max
BMI o	18.14473	4.908905	10.08769	116.4734
BMI y	17.388	5.892946	8.509078	116.4734
Height o	53.89779	7.849119	13	76
Height y	46.27293	8.747018	13	72
Weight o	1255.129	569.4895	336	3984
Weight y |	877.5823	438.4566	336	3280
Birth weight o	114.8652	20.59823	29	229
Birth weight y	116.8265	22.48571	6	248
Age o	9.403867	3.136103	2	19
Age y	6.38895	3.153716	2	17
Male o	.5049724	.5001134	0	1
Male y	.519337	.499764	0	1

Correlations

	BMI o	BMI y	Ht o	Ht y	Wt o	Wt y	BW o
BMI o	1.0000						
BMI y	0.3667	1.0000					
Height o	0.2783	0.0369	1.0000				
Height y	0.2505	-0.0793	0.7324	1.0000			
Weight o	0.6749	0.1648	0.8459	0.6423	1.0000		
Weight y |	0.3710	0.3213	0.6644	0.8492	0.6768	1.0000	
Birth weight o	0.0320	0.0025	-0.0285	-0.0692	0.0013	-0.0447	1.0000
Birth weight y	-0.0101	0.0098	-0.0265	-0.0383	-0.0191	-0.0058	0.4041

Table 2: NCLSY [Height 1990]

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	IV	IV	IV	GMM
DEP VAR	ΔLHT	LHT_m	LHT_m-$Q_m\tilde{\beta}_m$	LHT_f	LHT_f- $Q_f\tilde{\beta}_f$	ΔLHT, LHT
ΔAGE_m	0.121**					
	(0.0551)					
ΔLBW_m	0.0853**					
	(0.0396)					
$\Delta AGE_m \times LBW_m$	-0.0105					
	(0.00802)					
ΔAGE_f	0.224***					
	(0.0642)					
ΔLBW_f	0.144***					
	(0.0368)					
$\Delta AGE_f \times LBW_f$	-0.0203***					
	(0.00762)					
AGE_m		0.188***				0.256***
		(0.0700)				(0.00637)
LBW_m		0.128***				0.244***
		(0.0415)				(0.0103)
$AGE_m \times LBW_m$		-0.0184**				-0.0449***
		(0.00832)				(0.00129)
π_m			-0.0103			-0.131***
			(0.0519)			(0.00441)
AGE_f				0.259***		0.385***
				(0.0610)		(0.00660)
LBW_f				0.178***		0.408***
				(0.0347)		(0.0108)
$AGE_f \times LBW_f$				-0.0282***		-0.0705***
				(0.00700)		(0.00134)
π_f					-0.0217	0.0436***
					(0.0572)	(0.00594)
Observations	797	811	812	811	812	1608
R-squared	0.431	0.412	0.015	0.500	0.037	
Q_m & Q_f Exch		N	N	N	N	
IV rank test (pv)		0	0	0	0	
$\tilde{\beta}_m$=$\tilde{\beta}_f$ test (pv)	0.0234					
SD test (pv)		0.6535		0.5410		

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3: NCLSY [Weight 1990]

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	IV	IV	IV	GMM
DEP VAR	ΔLWT	LWT_m	LWT_m-$Q_m\tilde{\beta}_m$	LWT_f	LWT_f- $Q_f\tilde{\beta}_f$	ΔLWT, LWT
ΔAGE_m	0.00831					
	(0.100)					
ΔLBW_m	0.0674					
	(0.179)					
$\Delta AGE_m \times LBW_m$	0.0146					
	(0.0208)					
ΔAGE_f	-0.124					
	(0.129)					
ΔLBW_f	-0.233					
	(0.222)					
$\Delta AGE_f \times LBW_f$	0.0445*					
	(0.0267)					
AGE_m		-0.0742				-0.330***
		(0.0762)				(0.0201)
LBW_m		-0.0823				-0.270***
		(0.115)				(0.0318)
$AGE_m \times LBW_m$		0.0269*				0.0825***
		(0.0156)				(0.00415)
π_m			0.169			0.0119
			(0.195)			(0.0345)
AGE_f				-0.679***		-0.142***
				(0.128)		(0.0264)
LBW_f				-0.889***		-0.336***
				(0.185)		(0.0465)
$AGE_f \times LBW_f$				0.156***		0.0473***
				(0.0271)		(0.00549)
π_f					-0.520***	-0.665***
					(0.128)	(0.0434)
Observations	797	811	811	811	811	1508
R-squared	0.336	-0.423	-0.384	-0.550	0.713	
Q_m & Q_f Exch		N	N	N	N	
IV rank test (pv)		0	1.34e-06	0	0.000932	
$\tilde{\beta}_m$=$\tilde{\beta}_f$ test (pv)	0.4321					
SD test (pv)		0.0670		0.0004		

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: NCLSY [BMI 1990]

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	IV	IV	IV	GMM
DEP VAR	$\Delta LBMI$	$LBMI_m$	$LBMI_m$-$Q_m\tilde{\beta}_m$	$LBMI_f$	$LBMI_f$- $Q_f\tilde{\beta}_f$	$\Delta LBMI$, $LBMI$
ΔAGE_m	0.247*					
	(0.128)					
ΔLBW_m	0.131					
	(0.110)					
$\Delta AGE_m \times LBW_m$	-0.00567					
	(0.0224)					
ΔAGE_f	0.283**					
	(0.134)					
ΔLBW_f	0.197**					
	(0.0974)					
$\Delta AGE_f \times LBW_f$	-0.0166					
	(0.0199)					
AGE_m		0.412***				0.186***
		(0.0984)				(0.0115)
LBW_m		0.200***				0.325***
		(0.0635)				(0.0163)
$AGE_m \times LBW_m$		-0.0202				-0.0167***
		(0.0128)				(0.00233)
π_m			-0.0865***			-0.0970***
			(0.0315)			(0.00504)
AGE_f				0.314***		0.189***
				(0.117)		(0.0119)
LBW_f				0.198***		0.284***
				(0.0707)		(0.0168)
$AGE_f \times LBW_f$				-0.0172		-0.0157***
				(0.0146)		(0.00243)
π_f					0.0492	0.120***
					(0.0481)	(0.00846)
Observations	797	811	811	811	811	1608
R-squared	0.522	0.542	0.149	0.583	-0.087	
Q_m & Q_f Exch		N	N	N	N	
IV rank test (pv)		0	0	0	0	
$\tilde{\beta}_m$=$\tilde{\beta}_f$ test (pv)	0.2610					
SD test (pv)		0.6916		0.9767		

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$