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By

Michael G. Barnes, Trenton G. Smith, Jonathan K. Yoder

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Michael G. Barnes
Trenton G. Smith*
Jonathan K. Yoder

Washington State University

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Abstract

A number of recent studies have provided evidence suggesting that increases in body weight may spread via social networks. The mechanism(s) by which this might occur have become the subject of much speculation, but to date little direct evidence has been available. We provide evidence for one such mechanism: economic insecurity. Using a sample of working-age men from the National Longitudinal Survey of Youth, we show that cohabitation with working (but not non-working) adults appears to be protective against weight gain. We address the potential endogeneity of the independent variable by employing instrumental variables in our regression analysis.

Keywords: overweight, contagion, obesity, networks
JEL Codes: D12, I12

*Corresponding author: School of Economic Sciences, PO Box 646210, Washington State University Pullman, WA 99164-6210, USA (e-mail: trentsmith@wsu.edu)

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1 Introduction

Several recent studies have examined the possibility that obesity might be a product of one's social environment. In particular, studies of social networks have provided evidence suggesting that obesity is more likely when one has friends who are obese (Christakis and Fowler, 2007; Halliday and Kwak, 2009; Trogdon et al., 2008; Renna et al., 2008). These results appear to be somewhat robust to alternative econometric specifications, and have been reported in both adolescent and adult populations (Fowler and Christakis, 2008). While a number of plausible causal mechanisms (such as the propagation of body weight norms, unhealthy eating habits, smoking, and participation in sports) have been suggested, none has been tested directly.

In this paper, we provide direct evidence of an alternative mechanism that has gone unmentioned in the social networks literature, but which might plausibly explain the peer effects that have been reported. In particular, we explore the possibility that peers can provide a network of *financial* or *economic* support, which could then affect body weight via deep-seated psychological stress-response mechanisms. A broad interdisciplinary literature supports this putative relationship between economic insecurity and obesity (see Smith (2009)for a review), and Smith et al. (2009) have provided direct evidence for a relationship between income security and weight gain.

Substantial evidence suggests that social networks play an important role in the modulation of financial security through risk sharing and income pooling (Dekker, 2004; Hayashi et al., 1996; Altonji et al., 1992). The availability of effective social networks, moreover, may significantly decrease the likelihood of a household evaluating its food, economic, and housing conditions as vulnerable (Dershem and Gzirishvili, 1998). At the level of the household (the locus of our analysis), a potentially important component of financial security is likely to be risk-sharing among household members. One way to buffer against labor market risk or labor lost to illness, for instance, is through intra-household labor substitution, where large households with more workers can more easily compensate for lost income (Sauerborn et al., 1996; McKernan and Ratcliffe, 2005). Indeed, extended households are often formed to cope with the destructive consequences of poverty (Tienda and Angel, 1982) and to buffer against the economic effects of labor market risk (Angel and Tienda, 1982). There is also considerable evidence of food-sharing in response to risky foraging outcomes among modern hunter-gatherers (Gould, 1981; Kaplan and Hill, 1985; Cashdan, 1989), suggesting that the practice may have played an important role in human evolutionary history.

To examine these relationships, we estimate the effect of household composition–roughly measured as the number of workers and non-workers in the home–on individual weight, via its effect on financial insecurity. We do so using regression analysis to estimate the relationship between body weight and income characteristics, including both household composition and income insecurity measures, while controlling for other important personal and household factors.

In the next section we discuss hypotheses about the relationship between obesity and income characteristics. In Section 3.1 we develop an empirical model, describe the data, and discuss estimation issues. Section 3.2 includes the results and discussion. Section 4 concludes.

2 Household composition and obesity

An individual household member may the affect body weights of others in a household via effects on in-home production and consumption patterns within the home, but also via effects on the level and the risk profile of household income. Consider in particular the effect of having an additional income earner in the home. For a given wage distribution, this will tend to have an effect on both expected (or average) household income, and the variance of household income over time. The distinction between income *level* and income *variance*[1] is critically important.

First, the existing literature on the relationship between obesity and income suggests that the income level effect might increase body weights in the home *ceteris paribus*, to the extent that food intake is a normal good, and more income leads to more eating (Schroeter et al., 2008). However, changes in average or expected income can lead to changes in the quality of foods eaten as well. To the extent that people with higher income substitute toward more healthful (and perhaps less "fattening") foods (Drewnowski, 2007), weight and obesity increases might be offset to some extent. Similarly, income has an impact on the opportunity cost of time-intensive activities such as recreational exercise or making home-cooked meals, but this phenomenon (sometimes referred to as "time poverty") can afflict the poor as well as the rich (Vickery, 1977; Harvey and Mukhopadhyay, 2007). Thus, although it might be expected that income level is related to body weight, the direction of the effect of household income on weight is ambiguous.

Second, holding expected household income constant, the number of income earners in the household also has an effect on household income variance. This effect can be thought of in terms of the law of large numbers: as long as employment outcomes are not perfectly correlated, having additional incomes will tend to minimize the chances that realized per capita household income will see large deviations (e.g., all members losing their jobs at once) below its expected value. Implicitly, this assumes that household members pool at least some of their resources. Data limitations do not allow us the luxury of knowing whether workers actually pool income (though the literature cited in the previous section suggests many do), nor to specifically test the hypothesis that non-working adults contribute to household production and decrease the cost of eating healthy foods. Thus our estimates of the effects of household composition on body weight do not measure the effects of risk sharing or decreasing the relative price of a healthy lifestyle, but rather measure the *combined* effects of our specific measures of household composition on weight.

[1]For the purposes of this paper, we use the terms "income variance" and "income insecurity" interchangeably.

3 Empirical Analysis

In this section we develop an empirical model to estimate the effects of various measures of household composition and other individual-level measures on weight. We begin by presenting our model, followed by a discussion of the estimation procedure and the data, and end with a discussion of the results. A linear regression model is used to estimate the effects of household composition and other individual, demographic, and regional variables on weight. The available data (discussed in more detail below) include repeated observations over many individuals. The analysis focuses on weight in the year 2000, but relies on personal characteristics from 1994 to control for baseline characteristics and income security as discussed below. The regression equation takes the form

$$w_{2000,ij} = \alpha' \mathbf{h}_{2000,ij} + \beta' \mathbf{x}_{t,ij} + \eta_j + \varepsilon_{ij} \tag{1}$$

where $w_{2000,ij}$ is individual i's weight in year $t = 2000$, $\mathbf{h}_{2000,ij}$ is a vector of household composition characteristics in the home of individual i in region j, $\mathbf{x}_{t,ij}$ is a vector of individual characteristics for respondent i in *year* $t=$ 2000 or 1994, η_j is a regional fixed effect for region j, and ε_{ij} is a disturbance term for individual i. The data available for estimation are cross-sectional, so the estimate of the effects of household composition on weight in 2000 can be considered as the effect of differences across individuals on weight, controlling for the remaining variables. Measures of household composition and individual characteristics are explained in greater detail in the data section.

Equation (1) is linear in parameters, and in principle can be estimated via ordinary least squares (OLS). However, OLS as an estimator will be biased if weight is endogenously related to one or more of the independent variables. Reverse causality and unobserved personal characteristics that are correlated with body weight are both likely causes of endogeneity in our model. Reverse causation is present when weight exerts an influence on one of the right hand side variables. Cawley (2004), for example, finds that higher body weight correspond to lower wages for women. If true, the OLS estimate for income not only includes the effect of wages on weight, but the effect of weight on wages as well, making the estimate upward-biased. Bias relating to unobserved personal characteristics is present when weight gain is endogenously related to a right hand side variable. It could be, for example, that an individual who suffers from economic insecurity will gain weight, while also inviting others to live with him in an attempt to alleviate the effects of financial insecurity. In this case OLS estimates of α incorrectly include the effect of the latent variable "economic insecurity" and therefore will not represent the unbiased, causal effect of household composition on weight.

We correct for potential endogeneity bias in two ways. First, we include weight in 1994 in the model. Including 1994 weight in the model controls for permanent unobserved characteristics unique to the individual, as well as pre-1994 economic insecurity that may introduce bias into the estimates if omitted. 1994 weight is used because it allows us to examine the effects of household composition and other individual-level measures on changes in weight over a six-year time span. Also, 1994 is the most recent year that is not included in any of the other variables used in our regression (data from 1995 and later were used to construct the employment insecurity measures). Controlling for 1994 weight, however, does not eliminate bias occurring from events after 1994, nor for personal characteristics that change over time.

Second, to address the remaining potential for bias and inconsistency, we apply a Generalized Method of Moments (GMM) estimator, which uses instrumental variables to compensate for remaining endogeneity directly. This also facilitates the ability to flexibly address potential heteroskedasticity in the regression disturbances. For our instruments to be valid they must be: 1) highly correlated with the endogenous RHS variable of interest, 2) asymptotically uncorrelated with the errors, and 3) correctly excluded from the equation of interest (i.e., have no direct effects on weight). To test whether the instruments are highly correlated with the endogenous variables a test of instrument relevance is performed (also known as a weak instruments test). This test is based on the Kleibergen-Paap rk LM statistic (Kleibergen and Paap, 2006). The null hypothesis is that the model is under-identified, or that the smallest canonical correlation between the linear combinations of the independent variables and the instrument(s) is zero. Rejecting the test statistic indicates that the instruments pass the weak instruments test and are valid in this respect.

The other important instrument characteristic is that it be asymptotically uncorrelated with the regression disturbance (that is, the instrument itself is exogenous). The Hansen J-statistic (Hansen, 1982) is applied to test for exogeneity (equivalently, that the instruments are orthogonal to the regression disturbances). This test statistic is the GMM criterion function evaluated at the efficient GMM estimator, and it has a Chi-square distribution with degrees of freedom equal to the number of excluded instruments minus endogenous variables. This test is actually a joint test of the two requirements: exogeneity of the instrument and correct model specification (i.e., that the instruments are justly excluded). A large test statistic leads to rejecting the null hypothesis and indicates that the instruments do not satisfy the orthogonality conditions and are not valid.

3.1 Data and estimation

The data used in our analysis come from the National Longitudinal Survey of Youth, 1979 cohort (NLSY79). This survey follows 12,686 individuals born between 1957 and 1964. It was administered annually until 1993, and biennially since then. Although our study incorporates data from 1994-2000, the analysis is cross-sectional in nature. The nature of the dataset allows a comprehensive study of different measures of household composition for the respondent in 2000 as well as their personal experience with unemployment over the five-year period previous to 2000, and other individual level data.

Although women are included as members of the household in our analysis, they are not included as the measure of observation (the dependent variable) because the women in our sample are ages 29-42, peak child-bearing years. For this reason, women's weight may not be easily explained by measures of household composition or other individual-level data. Fertility decisions may also be related to any economic insecurity they face, and this complication would be difficult or impossible to address given our data limitations.

The primary variables of interest relate to financial insecurity. Three measures of personal unemployment are used: the posterior probability of unemployment in 2000, a dummy variable indicating whether the individual was unemployed at the time of interview in 2000, and a dummy variable indicating whether the individual was unemployed at any time in 2000. The posterior probability of unemployment is a proxy for an individual's perceived economic insecurity. This variable is formed using the last five years of weekly unemploy-

Table 1: Summary Statistics for Individual Characteristics, NLSY Men

Characteristic[1]	Mean	Standard Deviation[2]
Weight (in lbs) in 2000	197.121	39.069
Number of Workers in the Home	0.75	0.732
Number of Non-Workers in the Home	1.528	1.469
Ratio of Working Adults to Adults	0.301	0.254
Number of Children in the Home	1.299	1.321
Family Income	57.163	53.245
Posterior Probability of Unemployment	0.03	0.076
Unemployed at Any Time in 2000	0.119	–
Unemployed at Time of Interview in 2000	0.026	–
Currently Smoke	0.309	–
Weight (in lbs.) in 1994	187.708	35.872
Height in 1985 (in inches)	69.659	2.586
Height Squared in 1985	4859.127	358.576
Age	38.846	2.264
Black	0.274	–
Hispanic	0.184	–
White	0.542	–
Married	0.605	–
Divorce or separated	0.185	–
Widowed	0.004	–
Never Married	0.206	–
BA	0.219	–
Some College	0.216	–
High School Graduate	0.447	–
High School Dropout	0.117	–
Live Within a Metropolitan Area	0.728	–

[1] $N = 2880$.
[2] Variance for proportions of the binary variables is $p(1-p)$, where p is the reported mean of the binary variable.

ment history and represents an individual's perception of whether they will be unemployed the following year (for details see Smith et al., 2009). Previous evidence suggests that higher levels of insecurity correspond to weight gain. Unemployed at the time of the survey and unemployed anytime during the year are expected to have two distinct effects on weight as they measure different aspects of unemployment. An individual who happens to be unemployed on the day of the survey likely has a relatively low opportunity cost of healthy living because individuals that are not employed have more time to exercise and eat healthy foods, and thus might be expected to weigh less (Ruhm, 2000, 2005; Cutler et al., 2003). This variable is treated as exogenous as the particular day the individual is interviewed should not be related to unobserved personal characteristics. "Unemployed anytime during the year," however, indicates whether the individual faces unemployment risk based on having been unemployed in the past year and thus we treat it as endogenous. Individuals facing prospective unemployment risk are expected to weigh more. Means and standard deviations for all NLSY79 variables included in the analysis are presented in Table 1.

Our data include several measures of household composition. As explained above, we propose that these measures play a role in risk management as well as decreasing the relative price of healthy living. The household composition variables include: the number of workers in the home, the number of non-workers in the home, and the ratio of working adults to adults. The latter is included because the effect of workers may be different than working adults and working spouses. Subsets of these variables are included in different estimation specifications because the same instruments are used to estimate various measures of household composition and including them in the same regression makes it impossible to identify the distinct effects of these measures on weight.

The relationship of most interest is that between household income, income uncertainty, and weight, but several other personal characteristics that are expected to play a role in determining weight are included in the regressions as controls. They are: 1994 weight,[2] height in 1985, height squared in 1985,[3] age, race, marital status, years of schooling, a dummy variable indicating whether the respondent lives in a metropolitan area, and a dummy variable indicating whether the respondent smokes daily. Unless otherwise specified, variables are measured in the year 2000.

Approximately 75% of the individuals in our sample live with other people. The average weight for people that live with others is 198.1 pounds, compared to 194.1 for individuals that live alone. Nearly 61% of individuals in our sample live with someone who works. The average weight of people that live with someone who works is 199.8 pounds, while 192.9 is the average weight of people that don't live with workers. The average number of workers in the home in addition to the respondent is 0.75, with some homes having as many as five additional workers. The average number of workers in the sample for obese individuals is 0.82, while the average for non-obese people is 0.72. Furthermore, the average number of people in the home (in addition to the respondent) for obese people is 2.37, while the average for non-obese is 2.24. These statistics indicate that on average, higher weights correspond to more workers and more people in the home. Without correcting for endogeneity and controlling for other covariates, these raw correlations may incorrectly suggest that increasing the number of workers in the home causes weight gain, while in reality the relationship may be the other way around.

To further investigate the relationship between various measures of household composition and weight and economic security, consider the Pearson Correlation Coefficients for these relationships. The correlation coefficients between changes in weight to changes in measures of household composition (including the number of workers in the home and the number of people in the home) from 1998 to 2000 are less than 4%. The correlation coefficients between changes in unemployment and the same measures of household composition are 1% or less over the same time period. These statistics suggests that there is little statistical evidence that households invite additional workers (or non-workers) into the home to alleviate economic insecurity in the short term, implying that any bias relating to this aspect of endogeneity is likely very small.

Potentially endogenous variables include family income, unemployment risk, smoking, and household composition, and instrumental variables are used to address the endogeneity

[2]NLSY79 uses self-reported heights and weights. We correct for reporting error using NHANES III data, using the method described in Cawley (2004).

[3]1985 height is included because more recent reported measures of height are not available in NLSY79 (all respondents were at least 20 years old in 1985). Height and height squared are both included in order to allow for more flexible response relationships.

problem. State- and MSA-level instruments are used whenever possible to ensure that the instruments are exogenous to the errors and that they do not have an independent effect on weight. Because of limited data availability, however, we cannot rely solely on state- or MSA-level instruments to identify the effect of various measures of household composition on weight, so individual-level instruments are used as well. The use of individual-level instruments allows us to consistently estimate the effects of household composition on weight. Our instruments are as follows: State median household income from the U.S. Census Bureau is used as an instrument for family income. A time series of local unemployment rates in the respondent's MSA of residence are used as instruments for unemployment risk. A series of cigarette taxes (see Gruber and Frakes, 2006) are used as instruments for smoking. State median home prices from the U.S. Census Bureau, as well as the total number of adults in the home, are used to estimate the causal effect of the number of workers in the home on weight. The number of children in the home is used to identify the effect of non-workers in the home (although fertility may be dependent on unobserved personal characteristics and economic insecurity, the number of children in the home is arguably not affected by weight at any given time). Finally, county ethnicity percentages and the number of children in the home are used to identify the effects of adult non-workers on weight because evidence suggests that certain ethnicities are more likely to have more adults (e.g., grandparents and extended family members) in the home (Tienda and Angel, 1982; Angel and Tienda, 1982). The results of instrument validity tests are discussed in the next section along with the rest of the results.

3.2 Results

To provide a more complete examination of the relationships between household composition and weight, we perform regression analysis on several different model specifications. Results are presented in Table 2. Each column represents a different specification, differing from each other only in the variable(s) that are used to measure household composition and unemployment.

We fail to reject the Hansen J-Statistic in every specification, suggesting that the instruments used are unrelated to the error term, as required for consistent estimation. Results for this test are found in Table 3.[4] Our full suite of instruments, however, fails to pass the weak instruments test, implying that as a group they are not highly correlated with the endogenous variables. Family income was found to be the source of under-identification in the first specification, and smoking was found to be the source of under-identification (with cigarette taxes as the instruments) in regressions (2)-(4). Therefore, Table 3 reports the Kleibergen-Paap rk LM test statistics with corresponding p-values for two sets of regressions: regressions that treat these two sources of under-identification as endogenous, and test statistics for the regressions where the source of under-identification is treated as exogenous. The Hansen J-Statistic is not rejected at $\alpha = 0.05$ in any specification where the source of

[4] We estimated preliminary OLS regressions (not presented) for each of these specifications. Most of our endogenous variables switch signs from the expected (biased) sign in the OLS regression to the expected (unbiased) sign in the GMM regression, suggesting that the instruments used are likely valid (Hahn and Hausman, 2002). However, because multiple endogenous variables are used in each regression this may not necessarily be the case.

Table 2: Effect of Household Composition on Body Weight

Variables	(1)	(2)	(3)	(4)
Family income (in $1000)	0.0476*	0.0472	0.0471	0.0604***
	(0.028)	(0.034)	(0.033)	(0.019)
Unemployed at any time during	23.8274***	–	–	–
the Year	(5.346)			
Unemployed at time of Interview	-13.9714***	–	–	–
	(4.389)			
Posterior Probability	–	59.7271***	63.504***	67.8946***
of Unemployment		(23.098)	(23.499)	(9.801)
Number of Workers in the Home	–	-3.1469***	-2.7316***	–
		(1.051)	(1.038)	
Number of Non-Workers in the Home	–	–	-0.4212**	–
			(0.172)	
Ratio of Working Adults to Adults	–	–	–	-9.8802***
				(2.907)
Smoke Daily	-14.5259***	-7.6233	-7.5824	1.5167
	(3.998)	(5.303)	(5.228)	(3.031)
Weight in 1994 (in pounds)	0.9385***	0.9352***	0.9362***	0.9453***
	(0.012)	(0.013)	(0.013)	(0.010)
Height (in inches)	0.4234	-0.4199	-1.1735	3.2031
	(4.307)	(3.900)	(3.913)	(2.435)
Height (in inches) squared	0.0016	0.0086	0.014	-0.0188
	(0.031)	(0.029)	(0.029)	(0.018)
Age	-0.2291*	-0.0984	-0.1271	-0.1980*
	(0.133)	(0.138)	(0.135)	(0.114)
Black	2.6963***	3.0563***	3.068***	2.9989***
	(0.804)	(0.846)	(0.854)	(0.542)
Hispanic	-1.7962***	-0.7697	-0.5805	-0.8109
	(0.629)	(0.659)	(0.670)	(0.570)
Married	-0.3542	2.2664	2.6581	3.8241***
	(1.624)	(1.903)	(1.891)	(0.885)
Divorced or Separated	-1.4264	-1.3403	-1.2634	-1.2387
	(0.920)	(0.967)	(0.962)	(0.794)
Widow	1.9894	5.8011	6.2007	3.025
	(4.870)	(4.478)	(4.439)	(4.223)
BA Degree	-7.7437**	-5.3397	-5.3652	-1.4322
	(3.550)	(4.146)	(4.113)	(2.074)
Some College	-3.131	-1.4408	-1.5713	1.2403
	(2.186)	(2.257)	(2.239)	(1.173)
High School Graduate	-1.4331	-0.0729	-0.187	1.7692**
	(1.475)	(1.594)	(1.581)	(0.882)
Live Within a	0.5428	-0.1992	-0.1671	0.4515
Metropolitan Area	(0.631)	(0.512)	(0.514)	(0.379)
N	2541	2541	2541	2532
Adjusted R^2	0.729	0.759	0.759	0.752

Robust standard errors (adjusted for within-state clustering) in parentheses.
*significant at 10%, **significant at 5%, ***significant at 1%; Instruments are as follows:

Variable	Instrument(s)
Family income	State median household income
Posterior probability of unemployment	Local unemployment rates, 1988-2000
Unemployed any time during 2000	Local unemployment rates, 1988-2000
Smoke	Cigarette taxes, 1988-2000
Number of household workers	State median home prices, Number of adults in the home
Number of household non-workers	Number of children in the home

under-identification is treated as exogenous. We therefore report regressions that contain the original variables (rather than instrumented variables) in the regressions in which the instruments identifying the variable (family income and smoking, respectively) are weak. However, regardless of whether we utilize the weak instruments or use the original variables for income and smoking, respectively, the coefficients relating to our hypotheses about household composition and weight engender the same conclusions; they retain the same sign, retain statistical significance at conventional levels, and are different in magnitude by at most 29% of the value reported in Table 2.[5]

Table 3: Tests of Instrument Validity

	(1)	(2)	(3)	(4)
Tests of Over-Identification (Instrument Exogeneity)				
Null: Over-identifying restrictions are valid				
(Note: "Fail to Reject the Null" implies *valid* instruments)				
Hansen J statistic	16.36	24.14	23.56	28.03
χ^2 distribution p-value	0.56	0.19	0.21	0.3
Tests of Under-Identification (Instrument Relevance)				
Null: Equations are under-identified				
(Note: "Fail to Reject the Null" implies *invalid* instruments)				
Full set of instruments				
Kleibergen-Paap rk LM statistic	18.39	21.26	21.1	32.95
χ^2 distribution p-value	0.49	0.38	0.39	0.16
Treating sources of under-identification as exogenous				
Kleibergen-Paap rk LM statistic	32.772	23.89	24.33	30.49
χ^2 distribution p-value	0.02	0.01	0.01	<0.01

Columns index specifications as reported in Table 2.
Sources of under-identification, and their corresponding specifications:
Family Income (1), Smoke (2)-(4).

Given the richness of the available data relating to household composition of workers, non-workers, children and adults, there are many possible regressions specifications that could be reported. We present here a limited set that illustrates and reflects the general nature of these relationships. We begin our discussion of the regression results by focusing on the estimates for family income and the various measures of unemployment. Family income has a small but marginally significant effect on weight. Increasing income by $1000 increases weight by anywhere between 0.04 and 0.06 pounds, indicating that individuals are more likely to gain (not lose) weight as current income rises. Increasing an individual's posterior probability of unemployment by 0.01 increases weight by nearly a pound in some specifications. This

[5]The signs on the parameters associated with family income and smoking switch between the exogenous and endogenous treatment only once: for smoking in regression (4). Of all the other parameters in all four regressions combined, only 5 parameter estimates switch sign; but none of them were statistically significant in either regression, and none were directly related to the hypotheses regarding household composition on which this paper focuses.

result might appear to contradict Ruhm (2000, 2005), who finds that employment rates and body weight are positively related. Specification (1), however, reconciles these findings as we see that being *currently* unemployed has a negative effect on weight (the opportunity cost of time effect), while having been unemployed at any time over the year has a positive effect on weight (the insecurity effect). These findings suggest that weight is a function of both time costs and economic insecurity, as previously established. They also relate directly to the relationship between various measures of household composition and weight as workers are expected to affect weight through an increased security effect and contributors are expected to affect weight through a decreased time cost effect. We now study the effects of these and other measures of household composition on weight.

Specification (2) indicates that increasing the number of workers in the household by 1 person decreases weight by just over 3 pounds. We hypothesize that the increased security that accompanies more workers in the home is the mechanism driving the negative relationship with weight. As noted above, household workers serve as a financial safety net as intra-household labor substitutions minimize the effects of adverse economic shocks caused by illness, job loss, or a number of other factors.

Specification (3) indicates that both workers and non-workers have a negative effect on weight, with the effect of workers (the security effect) greater than the effect of non-workers (hypothesized to be a time cost effect). It should be noted that the effect of workers in this specification is smaller in magnitude (-2.73) than the effect in specification (2) (-3.14), implying that missing variable bias likely exists in the second specification because non-workers were not included. These results are consistent with our findings in specification (1), where various measures of unemployment are estimated. Specification (1) indicates that the effect of decreasing the relative cost of healthy living (being currently unemployed) decreases weight, while increasing insecurity (being unemployed anytime during the year) increases weight. In this regression, increasing the number of workers (increasing security) decreases weight, as does increasing the number of non-workers, or contributors to household production (perhaps by decreasing the relative cost of healthy eating).

Finally, specification (4) indicates that increasing the ratio of working adults to adults by one decreases weight by over 9 pounds. This would seem to provide further confirmation that employment status is of critical importance in determining the direction of the effects of cohabitation on body weight.

These empirical results offer insights into the effect of household composition on weight. First, living with others (having a social network in your home) decreases fattening. Evidence also suggests that in general, both workers and non-workers have a negative effect on weight. The effect of workers on weight is large and supports earlier findings (Smith et al., 2009; Barnes, 2008) that body weight increases with increasing economic insecurity.

4 Conclusion

The medical and epidemiological literature has examined the relationship between body weight and social networks, but has largely ignored the role that social networks play in the modulation of socioeconomic stressors such as income insecurity that are likely to have direct effects on body weight. Understanding the mechanisms at work in the apparent social "transmission" of obesity is of critical importance if policymakers are to develop an appropriate public health response.

Our results suggest that the reported peer effects on obesity in social networks could be an artifact, at least in part, of the underlying *economic* relationships between the individuals in question.

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