Depression and Consumer Demand: Evidence from Food Consumption in the U.S.

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Abstract

This paper expands the standard demand theory and uses cross-sectional data to investigate the relationship between depression and consumption. Our theoretical result is analogous to Slutsky's equation and establishes that a reduction in utility associated with higher levels of depression creates upward/downward pressure on the demand for inferior/normal goods. Using data from the U.S. National Health and Nutrition Examination Survey (NHANES) from 2007 to 2020, we empirically examine the implications of this result for food consumption. To address the endogeneity of depression caused by unobserved heterogeneity and reverse causality, we employ a heteroscedasticity-based identification approach. We find a positive association between depression and the percentage of calories intake from food categories classified as inferior. These results highlight the crucial role of mental health in influencing dietary habits in the U.S., with significant implications for nutrition and public health policies.

Keywords: Demand theory; Depression, Food consumption; Endogeneity.
JEL Codes: C21, D11, D12, D91.

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I. Introduction

Depression has significant socio-economic consequences. Globally, depression and anxiety are estimated to cost the economy one trillion US dollars per year (World Health Organization, 2019) and account for 8% of years lived with disability (Ridley et al., 2020). Greenberg et al. (2021) conducted a comprehensive study that estimated the total economic burden of major depressive disorder in the U.S. at $326.2 billion. This figure includes direct costs associated with the prevention, detection, treatment, and rehabilitation of depression. It also includes indirect costs representing the economic output lost due to morbidity and mortality associated with depression.

The symptom of disrupted food consumption, particularly the pathway to increased appetite and weight gain, is a major driver of the economic burden of depression. It directly fuels a cascade of expensive physical health comorbidities that amplify both direct medical costs and indirect productivity losses. Therefore, to address the economic burden of depression, a deeper theoretical and empirical understanding of its relationship with consumption is needed.

The paper is a significant addition to the expanding body of research in this area, as it employs a novel approach by integrating depression into the conventional consumer demand theory. This paper contributes to the emerging theoretical literature on the economic impacts of depression in behavioral economics. Existing research has examined the effect of depression on labor supply (De Quidt and Haushofer, 2016) and life cycle consumption (Strulik, 2019; Abramson et al., 2024).

Motivated by the psychiatric literature, we model depression as a negative shock to consumer utility. By incorporating depression into the standard consumer demand theory, we provide detailed comparative statics on how consumer demand will be affected by a change in depression based on the income effects of the good.

We show in a result similar to the Slutsky equation that the change in demand due to a change in depression can be decomposed into two components. The first is the change in the Hicksian demand due to the increase in depression. The sign of this component could be either positive or negative, depending on the characteristics of the good relative to depression. The second component is the change in the Marshallian demand relative to a change in income, multiplied by the change in utility with respect to depression and the change in expenditure relative to a change in utility. The sign of this effect is positive for inferior goods and negative for normal goods.

The intuition behind this result is that the disutility from depression enhances consumers' perception of income poverty because they are no longer able to achieve the same level of utility from an unchanged level of income. This feeling of a loss in income contributes to consumers increasing/decreasing their demand for inferior/normal goods.

This mechanism of perceived income poverty (feeling "poorer") is well documented in the psychiatric literature. For example, Beck and Alford (2009), in their pioneering book on depression, state that those suffering from the illness "feel that they are inadequate and not performing well, including in their financial lives, e.g., feeling that they are impoverished." In addition, when describing the emotional symptoms of

depression, they argue that severely depressed individuals may become preoccupied with being "completely impoverished" and that "attempts to correct these erroneous ideas are generally fruitless." The feeling of poverty can be so strong that it manifests as delusions or hallucinations. For example, Beck and Alford (2009) writes, "A wealthy patient may complain bitterly, All my money is gone. What will I live on? Who will buy food for my children?" These observations are consistent with depression causing an individual to feel poorer. In our model, this perceived income poverty contributes to an increase/decrease in the demand for inferior/normal goods.

Our paper also adds to the growing empirical literature on how mental disorders affect consumer behavior (Dahal and Fertig, 2013). For example, Meckel and Shapiro (2021) estimate the effect of depression on the composition of household grocery purchases. The authors find that households with at least one depressed member spend a smaller share of their consumption baskets on fresh produce and alcohol, and a larger share on tobacco.

We contribute to this body of literature by estimating the relationship between depression and food consumption, with food categories classified according to their income elasticity of demand. Using pooled data on food choices and calorie intake for the period 2007-2020 from the US National Health and Nutrition Examination Survey (NHANES), we provide empirical evidence that is consistent with our theoretical model. In particular, we find that depression is positively correlated with the share of calories consumed in food categories classified as inferior according to their income elasticity of demand. All food categories that exhibit a statistically significant correlation with depression show the expected sign, consistent with their income elasticity of demand. This suggests that the relationship between the income effect of a particular food category and depression is not driven by a single category.

To address the endogeneity of depression caused by unobserved heterogeneity such as genetics and reverse causality (Li et al., 2017; Molendijk et al., 2018), we employ a heteroscedasticity-based identification approach developed by Lewbel (2012). In the absence of instrumental variables, the approach exploits first-stage heteroscedasticity to construct alternative exclusion restrictions. The Lewbel's approach is an effective way to correct for the bias in ordinary least squares (OLS) estimates. Estimates from Lewbel's approach confirm that depression is positively/negatively correlated with calorie intake from food categories classified as inferior/normal. These results are consistent with the medical literature that finds that depression can significantly impact nutrition and food habits, often leading to overeating, particularly unhealthy "comfort foods," or a loss of appetite, resulting in inadequate calories intake, due to the complex interaction between mood, energy levels, and the desire to cope with negative emotions through food choices (Calcaterra et al., 2024; Ekinci and Sanlier, 2023; Paans et al., 2019).

Our model predicts that, all else being equal, an increase in the level of depression is associated with an increase/decrease in calorie intake from inferior/normal food and beverage categories. Since many unhealthy foods are inferior goods, our model provides a potential microfoundation for the positive association between depression and unhealthy calorie intake documented in the empirical literature.

The remainder of the paper is organized as follows. The next section presents

our theoretical model. Section 3 describes the data and the empirical model used to test the implications of our theoretical results. Section 4 presents the empirical results. Section 5 concludes.

II. Theoretical Analysis

The consumer utility function in this study takes the form $U(x, d)$, where $x \in \mathbb{R}^n$ is a quantity vector of n consumer goods and d is a parameter representing the level of consumer depression. We maintain the standard assumptions on the utility function (strict quasi-concavity and separability). With respect to depression, we assume only that utility is a decreasing function of depression: $\frac{\partial u(x,d)}{\partial d} < 0$. This assumption is consistent with the empirical literature on subjective well-being and mental health, which finds a negative correlation between depression and well-being (Steptoe et al., 2015; Kahneman and Krueger, 2006). The assumption is also consistent with the psychiatric literature on depression. According to the Diagnostic and Statistical Manual of Mental Disorders, to be diagnosed with depression, an individual must experience depressed mood and/or anhedonia, where anhedonia is the diminished ability to experience pleasure (American Psychiatric Association, 2013). In addition, psychiatrists describe the loss of subjective well-being as a primary feature of the illness (Beck and Alford, 2009). For example, Beck and Alford (2009) writes, "The loss of gratification is such a pervasive process among depressives that many patients describe it as the central feature of their illness." Furthermore, when describing the emotional symptoms of depression, Beck and Alford (2009) states that patients "exhibit a reduction in gratification, in the sense that they are unable to derive pleasure from activities they usually enjoy." These symptoms provide the rationale for modeling an increase in depression as a reduction in utility, holding all else constant.

The consumer's problem is to choose x to maximize utility, $U(x, d)$, subject to their budget constraint $px = w$, where p is a vector of prices and w is income:

$$\max_x \quad U(x, d)$$

Subject to:

$$px = w \quad \text{and} \quad x \geq 0$$

From this maximization problem, we obtain the Marshallian demand function, $x(p, w, d)$, and the indirect utility function, $V(p, w, d) = U(x(p, w, d), d)$. From the expenditure minimization problem, we can derive the Hicksian demand function, $h(p, \bar{u}, d)$, and the expenditure function, $e(p, \bar{u}, d)$, where $\bar{u}$ is a reference level of utility. Finally, using the Marshallian and Hicksian demand functions, we establish the following result:

Proposition 1. *The change in Marshallian demand for good i with respect to a change in depression, d, is given by the following equation:*

$$\frac{\partial x_i(p, d, w)}{\partial d} = \frac{\partial h_i(p, d, \bar{u})}{\partial d} + \frac{\partial x_i(p, d, w)}{\partial w} \frac{\partial e(p, d, \bar{u})}{\partial \bar{u}} \frac{\partial V(p, d, w)}{\partial d} \tag{1}$$

The proof of Proposition 1 can be found in the appendix. Proposition 1 states that the overall effect of depression on consumer demand can be decomposed into two effects. The first effect, $\frac{\partial h_i(p,\bar{u},d)}{\partial d}$, captures how a consumer changes their demand for good i based on the relationship between depression and the intrinsic characteristics of good i. Goods with certain characteristics may be more or less desirable to a consumer suffering from depression. For example, an increase in depression may increase a consumer's need for energy, causing them to seek out calorie-dense foods. If good i is a high-calorie food, then $\frac{\partial h_i(p,\bar{u},d)}{\partial d}$ may be positive. In addition, an increase in depression may make social interactions less enjoyable, thus reducing the Hicksian demand for goods that require extensive social interactions to consume, such as attending a movie in a crowded theater or a live sporting event. In this case, $\frac{\partial h_i(p,\bar{u},d)}{\partial d}$ would be negative.

The second term on the right-hand side of equation (1), $\frac{\partial x_i(p,d,w)}{\partial w}\frac{\partial e(p,d,\bar{u})}{\partial \bar{u}}\frac{\partial V(p,d,w)}{\partial d}$, implies that holding all else constant, an increase in depression raises demand for inferior goods ($\frac{\partial x_i(p,d,w)}{\partial w} < 0$) and lowers demand for normal goods ($\frac{\partial x_i(p,d,w)}{\partial w} > 0$). The magnitude of this effect is scaled by how much indirect utility declines in response to an increase in depression ($\frac{\partial V(p,d,w)}{\partial d} < 0$) and how much expenditure changes with respect to a change in utility ($\frac{\partial e(p,d,\bar{u})}{\partial \bar{u}} > 0$). An increase in depression reduces utility, making consumers feel less wealthy for a given level of income. This induces consumers to increase/decrease their demand for inferior/normal goods.

Graphical Depiction

In this section we illustrate the effects described by equation (1) graphically. Figure (1) illustrates the change in demand for a normal good, x in the figure, following an increase in depression from low ($d = L$) to high ($d = H$). Before the increase in depression, the utility-maximizing consumption bundle is at point C in the figure. This point is associated with a utility level of $\bar{u}$ from the indirect utility function $V(p, w, d = L)$ where p and w are prices and income respectively. When depression increases to $d = H$, consumption moves to point A, which is associated with a utility level of $\bar{u}'$ from the indirect utility function $V(p, w, d = H)$, where $\bar{u} > \bar{u}'$ by assumption. The movement from point C to A represents the total change in demand resulting from the change in depression.

Point B in the figure depicts expenditure minimizing bundle when depression is low ($d = L$) but utility is fixed at $\bar{u}'$, the level associated with high depression ($d = H$). The Hicksian demand at point B can be found by solving the expenditure minimization problem where utility is fixed at $\bar{u}'$. The income associated with point B, shown as the dashed line in the figure, represents the individual's "perceived income" when suffering from depression, whereas their "actual" income is given by the solid budget line. Note that the "perceived income" is less than the individual's "actual income", which is consistent with accounts of depressed individuals feeling impoverished even when they have sufficient income.

The "perceived income" is the income necessary to achieve the utility level when suffering from high depression, $\bar{u}'$, when depression is low, $d = L$. Including point B in

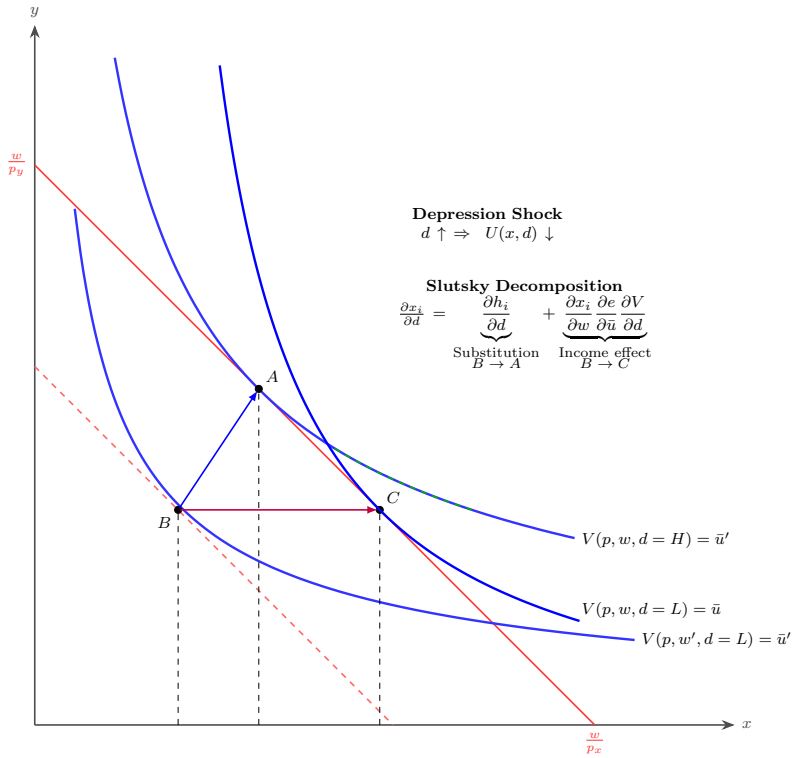


Figure 1: Effect of an Increase in Depression on Consumer Demand

the figure allows us to illustrate the two effects of a change in depression on demand that are described in equation (1). The movement from point B to point A represents the change in the Hicksian demand with respect to a change in depression, $\frac{\partial h_i(p,d,\bar{u})}{\partial d}$, as we are fixing utility at $\bar{u}'$ and varying the depression level. In the figure, we have drawn this to be positive for both goods x and y, but this could be zero or negative depending on where the utility function is tangent to the budget constraint under depression (point A).

The second term of equation (1), $\frac{\partial x_i(p,d,w)}{\partial w}\frac{\partial e(p,d,\bar{u})}{\partial \bar{u}}\frac{\partial V(p,d,w)}{\partial d}$, can be seen in the figure as the movement from B to C. This shift in the budget constraint represents the income effect, as the price ratio is fixed and we are shifting the budget constraint. Note that we have drawn x to be a normal good, as its consumption is increasing with income. The total effect (C to A) can be seen as the difference between these two effects.

III. Data and Empirical Model

The decomposition in Proposition 1 provides a testable implication of our theoretical framework. It establishes a precise channel through which depression affects consumption, generating an income effect that shifts demand towards inferior goods and away from normal goods by lowering utility. The primary objective of our subsequent empirical analysis is to provide a rigorous assessment of this core theoretical result. To achieve this, we will categorize food items according to their estimated income elasticity. We will then empirically test whether a higher level of depression is associated with a significant increase in the calorie share from goods classified as inferior and a decrease from those classified as normal. This will establish a direct link between our model's mechanism and an estimable relationship, enabling us to validate the theoretical income effect channel using real-world consumption data.

Data

To assess the empirical implications of our model, we use annual data on food consumption and depression from the National Health and Nutrition Examination Survey (NHANES) covering the period 2007-2020[1]. The NHANES is nationally representative of the total non-institutionalized civilian U.S. population. The survey questions used in this paper are included in the appendix. The pooled sample consists of 34,823 individuals with 524,371 food choice observations. Our outcome variable is the percentage of calories consumed from a particular food category. Since calorie intake is a weighted average of food intake, an implication of Proposition 1 is that an increase in depression, everything else being constant, will be associated with an increase in calorie intake from inferior foods. The opposite implication holds for normal food items.

To measure food choices and the associated calorie intake, survey participants were asked to recall their dietary intake over the past 24 hours. Data were collected

[1]This paper uses publicly available data from the National Health and Nutrition Examination Survey. The data can be downloaded from: https://wwwn.cdc.gov/nchs/nhanes/

via in-person interviews conducted in a private room, where survey respondents were provided with a set of measuring guides (e.g., glasses, bowls, household spoons, measuring cups, rulers, and visual aids) to help ensure accuracy when reporting quantities (CDC, 2008). Furthermore, to help filter out flawed dietary recall, we drop individuals who report consuming human breast milk. Despite these efforts to ensure accurate recall data, measurement error is possible. For example, Va et al. (2019) compares urine analysis to dietary recall data for a subset of the 2014 NHANES data and finds that survey respondents under report their consumption of sodium and potassium, but that the ratio of the two is unbiased. The authors note that this measurement error is problematic for dose response studies that attempt to estimate the associations between sodium and potassium intake and health outcomes (Va et al., 2019). Measurement error is less of a concern in our analysis, as we use food consumption as our outcome variable. Measurement error would be an issue in our setting if it were systematically related to our explanatory variable of interest, depression. In addition, our main outcome of interest is the percentage of calories consumed from inferior goods. If measurement error is consistent across food categories, then the ratio of food categories would be unbiased.[2] However, to the best of our knowledge, no evidence exists on the relationship between depression and measurement error or on how measurement error varies across food categories.

Food and beverage choices are classified according to the USDA's Food Surveys Research Group methodology. We organize food and beverage choices into 25 categories according to their 2-digit and 3-digit USDA food codes. These 25 subgroups and the corresponding USDA 2-digit and 3-digit codes are provided in Table A1 in the appendix. The data also includes the calorie intake associated with each food and beverage consumed. This allows us to calculate our main outcome variables, which are the calorie shares consumed from the various food categories. We then classify food categories as normal or inferior, based on estimates of income elasticities from an updated version of the USDA/ERS Commodity and Food Elasticity Dataset provided in Miao et al. (2013). These income elasticities estimates from Miao et al. (2013) remain empirically robust, as confirmed by recent studies from Chang (2023), Cessna et al. (2023), and Zereyesus et al. (2025). This consistency across a significant time span provides robustness to our classification. Table 1 includes the average, standard deviation, minimum, and maximum income elasticity for each food category, as obtained from Miao et al. (2013).

The survey also contains questions that allow us to construct the PHQ-9 index of depression. The PHQ-9 index is a widely used measure of depression and its severity (Kroenke and Spitzer, 2002; Kroenke et al., 2001; Spitzer et al., 1999). Table 2 presents the PHQ-9 depression categories and the percentage of people in each category. As seen in Table 2, 25.2% of our sample have some form of depression, where depression is defined as a PHQ-9 score greater than 4 (Kroenke et al., 2001). The majority of depression cases, 16.1%, are classified as mild, which corresponds to a PHQ-9 score between 5 and 9 (Kroenke et al., 2001). Finally, 3.5% of the sample are classified as having severe or moderately severe depression, corresponding to a PHQ-9 score greater

[2]This is the case for the ratio of sodium to potassium in Va et al. (2019).

Table 1: Income Elasticities by Food Category

	Income (Total Expenditure) Elasticity (Miao et al., 2013)			
	Mean	S.D.	Max	Min
Inferior Goods				
Creams	-0.13	0.12	0.02	-0.26
Milk desserts and sauces	-0.19	0.31	0.04	-0.41
Cheeses	-0.08	0.28	0.5	-0.41
Dry beans, legumes, and nuts	-0.36	0.15	-0.21	-0.51
Sugars and sweets	-0.2	0.29	0.19	-0.72
Coffee and tea	-0.27	0.17	-0.15	-0.39
Soft drinks, carbonated	-0.03	0.08	0.03	-0.09
Alcoholic beverages	-0.48	NA	-0.48	-0.48
Water	-0.2	NA	-0.2	-0.2
Normal Goods				
Milks and milk drinks	0.04	0.57	1.01	-0.56
Meats	0.78	0.43	1.57	-0.06
Sausages, lunchmeats, and organ meats	0.81	NA	0.81	0.81
Fish and shellfish	0.99	1.49	2.99	-0.48
Meat in mixtures	0.58	0.95	1.26	-0.09
Eggs	0.35	0.67	0.82	-0.12
Breads, crackers, and snacks from grain	0	0.54	0.73	-0.55
Cakes, pastries, and other grain products	0.13	NA	0.13	0.13
Pasta and Cereal	0.22	0.52	0.79	-0.23
Grain mixtures	0.58	0.95	1.26	-0.09
Fruit excluding juice	0.63	0.71	2.05	-0.47
Fruit juices	0.39	0.99	2.12	-1.36
Potatoes	0.29	NA	0.29	0.29
Other vegetables	0.19	0.3	0.8	-0.27
Fats	0.63	0.68	1.01	-0.68
Oils	0.44	0.52	1.03	0.05

Notes: This table presents the mean, minimum, and maximum of income elasticities reproduced from Table III in Miao et al. (2013). Goods are classified as inferior or normal according to the average income elasticity.

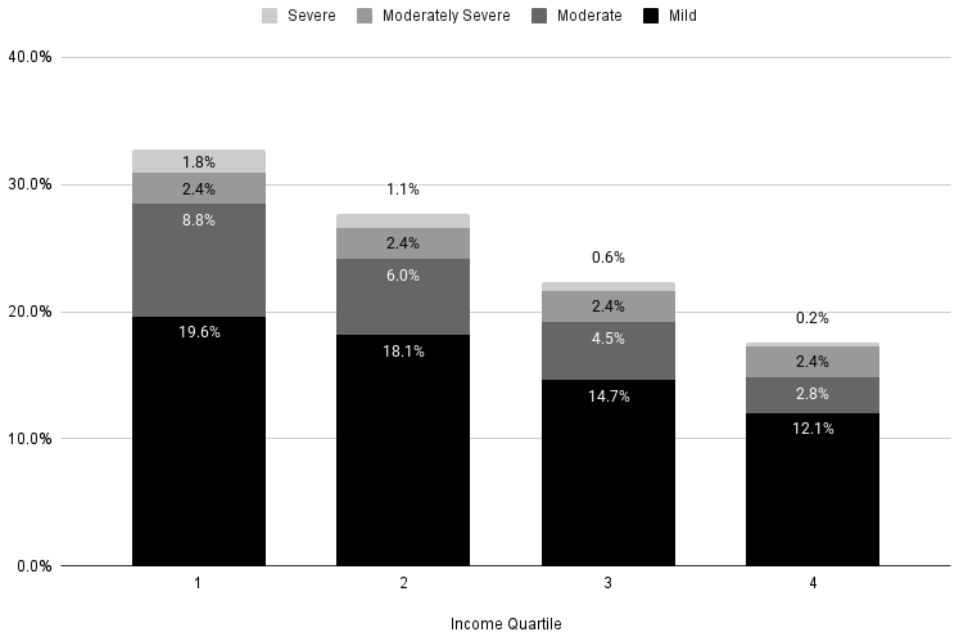
than 14. Figure 2 shows the percentage in each depression category for each income quartile. As seen in Figure 2, depression decreases with income, which underscores the role of income in mental health issues in the U.S. However, all severity levels are present in each income quartile.

Table 2: Severity of Depression

	PHQ-9	%	S.D.
Depressed	>4	25.2%	0.43
Mild	5-9	16.1%	0.37
Moderate	10-14	5.7%	0.23
Moderately Severe	15-19	2.5%	0.15
Severe	>19	1.0%	0.1

Notes: The table displays the percentage of respondents in each depression category. Depression categories are classified according to the PHQ-9 index.

Figure 2: Prevalence of Depression by Income Quartile



Notes: The figure displays the percentage for each depression category by monthly family income quartile. The income quartiles are categorized as follows: Q1: 0-1,649 , Q2: 1,649-2,899, Q3: 2,899-5,399, Q4: greater than 5,400. The percentages listed in each bar represent the percentage in each depression category. Depression categories are classified according to the PHQ-9 index as follows: mild: 5-10, moderate: 10-15, moderately severe: 15-20, severe: greater than 20.

Empirical Model

We now turn to the empirical model used to estimate the relationship between depression and food consumption. Specifically, we estimate the following linear models:

$$C_{ij} = \beta_j D_i + X_i^{'} \alpha_j + u_i. \tag{2}$$

Where C_{ij} is the share of calories consumed by individual i from food category $j \in \{1, ..., J\}$. J is the total number of food categories considered and classified as inferior or normal goods. D_i is the PHQ-9 depression index for individual i, X_i is a vector of exogenous individual and household level characteristics associated with individual i including: height, weight, body mass index, sex, age, age squared, family size, age of household head, age of household head squared, marital status, ethnicity fixed effects, education of the household head fixed effects, household income quartiles fixed effects, a dummy variable indicating whether the individual is on a special diet, the number of meals not prepared at home, the number of ready-to-eat foods eaten in past 30 days, and the number of frozen meals/pizza in past 30 days. u_i is the econometric error term. The parameter of interest is β_j, which measures the relationship between depression and calorie intake from the food category j. Our theoretical results imply that β_j is positive if j is an inferior good and negative if j is a normal good.

Using ordinary least squares (OLS) to estimate 2 would result in a biased estimate of β_j due to unobserved heterogeneity and reverse causality. The empirical literature on nutrition shows that diet can affect the onset of depression (Li et al., 2017; Molendijk et al., 2018). Poor nutrition can lead to short- and long-term depression through mechanisms such as inflammation (Eltokhi and Sommer, 2022), microbiome disruption (Simpson et al., 2021), and nutrient deficiencies (Jacka et al., 2017). On the other hand, high sugar/fat diets can lead to short-term mood improvement through neurochemical effects, since sugar triggers the release of dopamine and serotonin (Benton, 2002), and brain reward pathways (Ulrich-Lai et al., 2010). Conversely, depression can cause poor diet through mechanisms such as emotional eating, appetite dysregulation, and reduced motivation. Due to neurobiological (for example, search for serotonin) or behavioral (for example, low motivation to cook) mechanisms, depression can increase cravings for high sugar/fat "comfort foods" leading to a positive effect of depression and unhealthy diet. The existence of this bidirectional relationship suggests the presence of a negative bias in the OLS estimate of β_j for unhealthy food categories.

We cannot use fixed effects models to address simultaneity, since these models require panel data. However, we could use standard instrumental variable (IV) or control function strategies to address this bias by identifying a variable that influences calorie intake solely through its impact on depression. One potential option would be to use polygenic risk scores. Unfortunately, such variables are not available in our dataset. To address the endogeneity issue in the absence of instrumental variables, therefore, we implement a heteroscedasticity-based identification approach developed by Lewbel (2012). The intuition behind this approach is presented below. Given that depression

D is an endogenous variable, we have:

$$D_i = X_i^{'}\gamma + v_i, \tag{3}$$

where the error terms u and v may be correlated. We assume that there is a subset of elements of X, Z, so that: (a) $Cov(Z, uv) = 0$ and (b) $Cov(Z, v^2) \neq 0$ (v is heteroscedastic). The estimator of β_j is obtained in two steps:

- estimate $\hat{\gamma}$ by OLS and compute the residuals $\hat{v}_i = D_i - X_i^{'}\hat{\gamma}$,
- estimate β_j and α_j by applying two-stage least squares to equation 2 using $(Z - \bar{Z})\hat{v}$ as instruments for D.

Baum and Lewbel (2019) provide sufficient conditions for assumptions (a) and (b) to hold. We now discuss the validity of these conditions in our empirical application. We consider the subset of characteristics Z consisting of age, age squared, sex, height, ethnicity, household income, education of the household head, age of the household head, and age of the household head squared. The first condition is the presence of an unobserved factor ϵ that affects both depression and calorie intake from food. As discussed in Eltokhi and Sommer (2022), unobserved gut microbiota satisfies this condition. The second condition is that ϵ^2 is uncorrelated with Z. Failing to reject the homoskedasticity of u conditional on Z is enough to ensure the validity of this condition. Finally, the third condition is that v^2 is correlated with Z, which is true if v is heteroscedastic conditional on Z. Given our vector Z, the model in equation 2 is overidentified, and we can perform standard overidentification J-tests to provide further support for Lewbel's approach. A J-test with a p-value greater than 5% suggests that overidentification cannot be rejected and supports the use of the approach.

IV. Empirical Results and Discussion

Table 3 presents the estimates of equation 2. The first row shows the estimates when the outcome variable is the share of calories consumed from all food categories classified as inferior (percent inferior). In the remaining rows, the outcome variable is the share of calories consumed from each food category considered. Columns (1) and (2) present the OLS estimates (coefficients and standard errors), while columns (3)-(5) present Lewbel's approach estimates. Looking at the first row, as suggested by our theory, depression is positively correlated with percent inferior. The coefficient of the depression index in column (1) indicates that an increase in the index by ten points is associated with an average increase in the share of calories consumed from food classified as inferior by 2.7%. The estimate for Lewbel's approach, column (3), is larger at 0.39, which is consistent with the OLS estimates being biased downward.

The results presented in the remaining rows are generally consistent with our theory, with inferior/normal goods being positively/negatively correlated with depression. For Lewbel's approach estimates, we find a positive and statistically significant coefficient on the depression index for the inferior categories: creams, sugars and sweets,

Table 3: The Effect of Depression on Percentage of Calories Consumed

			Lewbel's Approach		
	PHQ	S.E.	PHQ	S.E.	J test p-value
	(1)	(2)	(3)	(4)	(5)
Percent Inferior (Aggregate)	0.27***	0.03	0.39***	0.07	0.301
Inferior Goods					
Creams	0.02***	0.00	0.03**	0.01	0.841
Milk desserts and sauces	0.01	0.01	0.00	0.02	0.126
Cheeses	-0.01	0.01	-0.02	0.02	0.259
Dry beans, legumes, and nuts	-0.03·	0.01	0.03	0.03	0.378
Sugars and sweets	0.08***	0.01	0.09***	0.03	0.85
Coffee and tea	0.03***	0.01	0.05*	0.03	0.438
Soft drinks, carbonated	0.13***	0.01	0.15***	0.04	0.032
Alcoholic beverages	0.03*	0.02	0.06	0.04	0.017
Water	0.00	0.00	0.00	0.00	0.366
Normal Goods					
Milks and milk drinks	0.02	0.01	0.01	0.03	0.979
Meats	-0.07***	0.02	-0.09**	0.04	0.427
Sausages, lunchmeats, and organ meats	-0.00	0.01	-0.03	0.02	0.09
Fish and shellfish	-0.03**	0.01	0.00	0.02	0.73
Meat in mixtures	0.01	0.02	0.03	0.06	0.332
Eggs	-0.02*	0.01	-0.04*	0.02	0.863
Breads, crackers, and snacks from grain	-0.05*	0.02	0.02	0.05	0.671
Cakes, pastries, and other grain products	-0.01	0.02	-0.03	0.04	0.011
Pasta and Cereal	-0.03*	0.01	0.03	0.04	0.006
Grain mixtures	-0.02	0.03	-0.09	0.07	0.979
Fruit excluding juice	-0.04***	0.01	-0.07***	0.02	0.032
Fruit juices	0.01	0.01	0.00	0.03	0.138
Potatoes	-0.01	0.01	-0.01	0.03	0.417
Other vegetables	-0.03***	0.01	-0.03*	0.02	0.521
Fats	-0.00	0.00	-0.01*	0.01	0.677
Oils	-0.01	0.01	-0.03*	0.01	0.256
Controls	Yes		Yes		
Observations	21,285		21,285		

Notes: All coefficients and standard errors are multiplied by 100. The outcome variables are the percentage of calories from each category. The columns labeled PHQ, (1) and (3), presents the coefficient on the depression index followed by it's standard error. All regressions include the following controls: height, weight, BMI, sex, age, age squared, age of household head, age of household head squared, family size, marital status, ethnicity fixed effects, income quartile fixed effects, education of household head fixed effects, # of ready-to-eat foods in past 30 days, # of meals not home prepared, # of frozen meals/pizza in past 30 days, an indicator for being on a special diet. Columns (3) to (5) presents the results from Lewbel's Approach. The instruments include: age, age squared, sex, height, ethnicity fixed effects, household income fixed effects, education of household head fixed effects, age of household head, age of household head squared. Goods are classified as inferior or normal according to the average income elasticity from Table III in Miao et al. (2013). *** p<0.001, ** p<0.01, * p<0.05.

coffee and tea, and soft drinks. For normal goods, Lewbel's approach estimates show that a depression has a negative and statistically significant association with consumption of: meats, eggs, fruit excluding juice, other vegetables, fats and oils.

Our empirical finding that depression is associated with an increased consumption of inferior and often less healthy foods is consistent with well-established psychological and behavioral mechanisms. The income effect channel from our model provides an economic framework for these pathways. Firstly, impaired emotional regulation, a core symptom of depression, can lead to an increased reliance on high-sugar, high-fat comfort foods as a form of self-medication, providing temporary mood elevation via neurochemical rewards (e.g. dopamine release). Since many of these foods are inferior goods, this manifests as the predicted positive demand shift. Secondly, depression can heighten the physiological stress response, increasing cravings for energy-dense foods while reducing cognitive bandwidth for meal planning. This favors convenient, inexpensive and palatable inferior options. Thirdly, depression has been associated with time inconsistency and present bias, which reduces the valuation of future health benefits and increases the immediate gratification derived from unhealthy foods. This shortsightedness effectively lowers the implicit price of negative long-term health consequences, making inferior, unhealthy goods relatively more attractive. Thus, the perceived income loss in our model can be viewed as an economic analogue to the psychological resource depletion and diminished future orientation that are characteristic of depression. These factors systematically alter dietary choices towards inferior goods.

Column (5) presents the p-values from the Hansen J test used to assess the validity of Lewbel's approach, under the assumption that the model is overidentified. Note that the p-value for our aggregate category, percent inferior, is well above the threshold value of .05. This implies that there is no evidence against the validity of Lewbel's approach. For the regressions at the food category level, we see that the majority of the p-values are above the .05 threshold, providing support for our heteroscedasticity-based identification strategy. However, there are some categories where this criterion is not satisfied.[3] For these categories, the constructed instruments could affect the proportion of calories consumed directly, through pathways other than depression, or they could be correlated with the error due to model misspecification. This could suggest a more complex relationship with depression than is fully captured by our core income-effect channel. The association between alcoholic beverages and depression is notoriously bidirectional and confounded by unobserved genetic, social and behavioral factors (McHugh and Weiss, 2019; Kim et al., 2024), which may not satisfy the exclusion restrictions required by our identification strategy, even after accounting for heteroscedasticity. The consumption of cakes and pastries for example may be heavily influenced by context-specific emotional eating or cultural norms interacting with depression in ways not fully captured by our constructed vector of instruments, Z. These goods could occupy an ambiguous position where their classification as normal goods, based on ag-

[3]These categories include: "Soft drinks, carbonated", "Alcoholic beverages", "Sausages, lunchmeats, and organ meats" , "Cakes, pastries, and other grain products" , "Pasta and Cereal", "Fruit excluding juice."

gregate income elasticity, masks situational inferiority for individuals experiencing acute psychological distress. This could lead to model misspecification for these specific categories. However, these exceptions do not invalidate the broader pattern that supports our theoretical framework, but they might suggest that, for certain food categories, the depression-demand relationship is mediated by additional unmodeled psychological or neurobiological pathways that could be disentangled by future research.

Finally, the observed association between depression and poorer dietary patterns, including higher consumption of unhealthy foods, is corroborated by a growing body of international evidence. Research in diverse Western populations demonstrates a consistent link. In a cross-European sample, Paans et al. (2018) found that both a history and a higher severity of depression were associated with more emotional and uncontrolled eating. Similarly, in Australia, Jacka et al. (2015) observed that individuals with current depressive symptoms had a lower adherence to a healthy dietary pattern. Longitudinal data from Canada adds causal nuance; Gougeon et al. (2017) reported that the onset of depression in older adults was followed by a significant decline in the quality and quantity of nutrient intake. Furthermore, a dose-response relationship has been identified, as evidenced by work in the Netherlands showing that more chronic and severe depression and anxiety disorders are associated with progressively poorer diet quality (Gibson-Smith et al., 2018). Collectively, these international findings underscore that the relationship observed in the U.S. context is not isolated, but rather reflects a broader public health phenomenon wherein depression is robustly linked to less healthy food consumption across multiple countries and cultural settings.

Robustness

In this section, we explore whether the results are robust to alternative measures of depression. To do so, we replace the PHQ variable with a binary variable that equals one if the PHQ score exceeds a specific threshold. We consider four severity levels of depression, following (Kroenke et al., 2001): mild (PHQ $\geq$ 5), moderate (PHQ $\geq$ 10), moderately severe (PHQ $\geq$ 15), and severe (PHQ $\geq$ 20). Table 4 presents the estimates of equation 2 for each depression category.

As shown in the table, for all categories of depression, the coefficients of the depression indicator variables are positive and statistically significant for both the OLS estimates (columns 1 and 2) and Lewbel's approach estimates (columns 3-5). Moreover, the p-values for the J test are all well above the threshold of 0.05. Note also that the magnitudes of the coefficients increase as the depression threshold rises. For example, for the instrumental variable estimates, the coefficient when depression is classified as severe is approximately double the coefficient when the lowest depression threshold (mild or greater) is used.

These results are consistent with our theory. In equation 1, the wealth effect, $\frac{\partial x_i(p,d,w)}{\partial w}$, is multiplied by the term $\frac{\partial e(p,d,\bar{u})}{\partial \bar{u}} \frac{\partial V(p,d,w)}{\partial d}$. The term $\frac{\partial V(p,d,w)}{\partial d}$ represents the change in indirect utility with respect to a change in depression. For severe depression, we expect the decrease in utility to be much larger than when depression is classified as mild or greater. Holding all else constant, a larger decrease in utility caused by

depression exerts greater upward or downward pressure on the demand for inferior or normal goods, respectively.

In the appendix, for each depression category, we include estimates for different food categories in Tables A2, A3, A4, and A5. The results are qualitatively similar to those in Table 3. In particular, all statistically significant coefficients on the depression variable have the expected sign, with goods classified as inferior or normal having positive or negative coefficients, respectively.

Table 4: The Effect of Depression Categories on Percentage of Calories Consumed

			Lewbel's Approach		
	Dep.	S.E.	Dep.	S.E.	J test p-value
	(1)	(2)	(3)	(4)	(5)
Mild (PHQ $\geq$ 5)					
Percent Inferior	2.15***	0.25	3.31***	1.02	0.168
Percent Depressed	25.24				
Moderate (PHQ $\geq$ 10)					
Percent Inferior	3.26***	0.38	4.56***	0.81	0.207
Percent Depressed	9.13				
Moderately Severe (PHQ $\geq$ 15)					
Percent Inferior	4.22***	0.59	5.49***	1.10	0.696
Percent Depressed	3.47				
Severe (PHQ $\geq$ 20)					
Percent Inferior	4.84***	1.08	6.64***	2.05	0.672
Percent Depressed	1.00				

Notes: This table presents the OLS and IV estimates for alternative depression cut-offs. Dep. represents the depression indicator variable. All coefficients and standard errors are multiplied by 100. The outcome variable is the percentage of calories from inferior goods. Columns (1)-(2) report OLS estimates and columns (3)-(5) report instrumental variables estimates. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

V. Conclusion

This paper examines the relationship between depression and consumer demand. We incorporate depression into the utility function in the standard consumer demand theory and demonstrate that the reduction in utility caused by depression triggers an income effect on consumers, which, in turn, induces upward/downward pressure on the demand for inferior/normal goods. Using data from the U.S. National Health and Nutrition Examination Survey (NHANES), we illustrate the implications of this result for food consumption. The heteroscedasticity-based identification approach allows us to estimate the effect of depression on food calorie intake while accounting for depression's endogeneity and controlling for various socioeconomic and cultural factors. Our findings show that depression is positively correlated with the percentage of daily calories

obtained from food categories classified as inferior.

These results suggest the need for an integrated policy approach that addresses mental health and nutrition issues simultaneously. Cross-sectoral policies that target both mental health and nutrition could improve public health outcomes. This requires merging mental health and nutritional interventions, such as embedding dietary screening in depression care and designing food assistance programs that make healthy choices easier and cheaper for vulnerable individuals (Opie et al., 2017). Mental health initiatives in schools, hospitals, and workplaces could include subsidized healthy and nutrient-dense meals (Lassale et al., 2019), and public health messaging should frame nutrition as mental self-care. Ultimately, treating depression is a form of food policy, and improving food access is a form of mental healthcare, demanding coordinated action across health, social welfare, and economic regulation.

One limitation of this study is that it used cross-sectional data. In future work, we plan to expand upon our results by using a dynamic consumer demand model and panel data to investigate the dynamic effects of depression on food consumption and explore potential underlying mechanisms. This would enable lagged effects, adjustment speeds, and cumulative exposure to be modeled directly, allowing the distinction to be made between dietary changes driven by acute depressive episodes and those driven by chronic conditions. Furthermore, methods such as fixed effects or dynamic panel models would offer greater control over unobserved time-invariant heterogeneity, thereby strengthening causal claims, and providing critical evidence for the timing and persistence of effects needed to design effective, well-targeted public health interventions.

Author contributions

CRedit: **Ian Heffernan:** Conceptualization, Formal analysis, Methodology, Software, Visualization, Data analysis, Writing - original draft, Writing - review & editing; **Karim Nchare:** Formal analysis, Methodology, Software, Visualization, Data analysis, Writing - original draft, Writing - review & editing.

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Data availability statement

Data will be made available on request.

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VI. Appendix

A1. Proof of Proposition 1

Proof of Proposition 1: Using the dual relationship between the utility maximization and expenditure minimization problems (Mas-Colell et al., 1995), we have:

$$h_i(p, d, \bar{u}) = x_i(p, d, e(p, d, \bar{u}))$$

taking the derivative of both sides with respect to d:

$$\frac{\partial h_i(p, d, \bar{u})}{\partial d} = \frac{\partial x_i(p, d, e(p, d, \bar{u}))}{\partial d} + \frac{\partial x_i(p, d, e(p, d, \bar{u}))}{\partial e(p, d, \bar{u})} \frac{\partial e(p, d, \bar{u})}{\partial d}$$

Using the envelope theorem, we can show that:

$$\frac{\partial e(p, d, \bar{u})}{\partial d} = -\lambda \frac{\partial V(p, d, w)}{\partial d} \tag{4}$$

where λ is the Lagrange multiplier from the expenditure minimization problem. Applying the envelope theorem to the expenditure minimization problem we can also show $\lambda = \frac{\partial e(p,d,\bar{u})}{\partial \bar{u}}$. We can then rewrite equation (4) as:

$$\frac{\partial e(p, d, \bar{u})}{\partial d} = \frac{\partial e(p, d, \bar{u})}{\partial \bar{u}} \frac{\partial V(p, d, w)}{\partial d} \tag{5}$$

Finally, using $e(p, d, V(p, d, w)) = w$ and re-arranging we can obtain:

$$\frac{\partial x_i(p, d, w)}{\partial d} = \frac{\partial h_i(p, d, \bar{u})}{\partial d} + \frac{\partial x_i(p, d, w)}{\partial w} \frac{\partial e(p, d, \bar{u})}{\partial \bar{u}} \frac{\partial V(p, d, w)}{\partial d}$$

□

A2. Tables

Table A1: USDA Food Category Classifications

Food Category	USDA Code
Creams	12
Milk desserts and sauces	13
Cheeses	14
Dry beans, legumes, and nuts	41−43
Sugars and sweets	91
Coffee and tea	921−923
Soft drinks, carbonated	924
Alcoholic beverages	93
Water	94
Milks and milk drinks	11
Meats	20−24
Sausages, lunchmeats, and organ meats	25
Fish and shellfish	26
Meat in mixtures	27, 28, 77
Eggs	31-35
Breads, crackers, and snacks from grain	51, 52, 54
Cakes, pastries, and other grain products	53, 55
Pasta and Cereal	56, 57
Grain mixtures	58, 59
Fruit excluding juice	61-67, excluding 612, 641, 642, 644
Fruit juices	612, 641, 642, 644, 92
Potatoes	71
Other vegetables	72−76
Fats	81
Oils	82, 83

Notes: Food categories and the corresponding two and three digit USDA code as used in (Miao et al., 2013).

Table A2: Severe Depression (PHQ $\geq$ 20): Percentage of Calories Consumed

			Lewbel's Approach		
	PHQ	S.E.	PHQ	S.E.	J test p-value
	(1)	(2)	(3)	(4)	(5)
Percent Inferior (Aggregate)	4.84***	1.08	6.64***	2.05	0.672
Inferior Goods					
Creams	0.15	0.18	0.31	0.34	0.265
Milk desserts and sauces	0.26	0.38	0.29	0.70	0.677
Cheeses	-0.38	0.33	-0.62	0.49	0.224
Dry beans, legumes, and nuts	-0.78	0.55	-0.74	0.64	0.247
Sugars and sweets	1.85***	0.40	1.77*	0.97	0.881
Coffee and tea	1.32***	0.33	1.93**	0.94	0.151
Soft drinks, carbonated	2.48***	0.52	3.17**	1.34	0.725
Alcoholic beverages	-0.08	0.65	0.51	1.13	0.398
Water	0.01	0.05	0.02	0.10	0.423
Normal Goods					
Milks and milk drinks	0.96	0.49	0.22	0.96	0.311
Meats	-1.14	0.74	-1.67*	0.95	0.750
Sausages, lunchmeats, and organ meats	-0.22	0.37	-0.08	0.47	0.367
Fish and shellfish	-0.53	0.40	-0.16	0.66	0.240
Meat in mixtures	0.50	0.96	2.42	1.54	0.446
Eggs	-1.22**	0.41	-1.54***	0.38	0.082
Breads, crackers, and snacks from grain	-1.31	0.80	-1.95*	1.11	0.565
Cakes, pastries, and other grain products	0.46	0.72	-0.36	1.22	0.083
Pasta and cereal	-0.40	0.58	-0.23	1.08	0.591
Grain mixtures	-0.38	1.20	-0.30	1.61	0.257
Fruit excluding juice	-0.70	0.36	-0.85*	0.49	0.418
Fruit juices	-0.13	0.46	-0.97	0.64	0.301
Potatoes	-0.45	0.54	-0.34	0.67	0.327
Other vegetables	-0.58	0.35	-0.28	0.41	0.340
Fats	-0.13	0.15	-0.25	0.17	0.907
Oils	-0.60*	0.27	-0.90***	0.26	0.098

Notes: All coefficients and standard errors are multiplied by 100. The outcome variables are the percentage of calories from each category. Columns (1)â(2) report OLS estimates. Columns (3)â(5) report estimates using Lewbelâs approach. Goods are classified as inferior or normal according to the average income elasticity from Table III in Miao et al. (2013). $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table A3: Moderately Severe Depression (PHQ $\geq$ 15): Percentage of Calories Consumed

			Lewbel's Approach		
	PHQ	S.E.	PHQ	S.E.	J test p-value
	(1)	(2)	(3)	(4)	(5)
Percent Inferior (Aggregate)	4.22***	0.59	5.49***	1.10	0.696
Inferior Goods					
Creams	0.44***	0.10	0.80***	0.29	0.475
Milk desserts and sauces	0.33	0.21	0.29	0.37	0.633
Cheeses	-0.14	0.18	-0.09	0.33	0.414
Dry beans, legumes, and nuts	-0.05	0.30	0.51	0.46	0.928
Sugars and sweets	1.01***	0.22	1.23***	0.45	0.795
Coffee and tea	0.50**	0.18	0.90**	0.42	0.524
Soft drinks, carbonated	2.26***	0.29	2.11***	0.72	0.663
Alcoholic beverages	-0.12	0.36	-0.22	0.58	0.185
Water	-0.01	0.03	-0.04	0.04	0.107
Normal Goods					
Milks and milk drinks	0.23	0.27	-0.04	0.47	0.380
Meats	-0.75	0.41	-1.06*	0.60	0.810
Sausages, lunchmeats, and organ meats	-0.33	0.20	-0.59*	0.34	0.630
Fish and shellfish	-0.06	0.22	0.18	0.45	0.894
Meat in mixtures	0.11	0.53	-0.21	0.86	0.526
Eggs	-0.41	0.23	-0.61	0.39	0.666
Breads, crackers, and snacks from grain	-0.75	0.44	-0.77	0.69	0.708
Cakes, pastries, and other grain products	-0.45	0.39	-0.69	0.64	0.115
Pasta and cereal	-0.15	0.32	0.60	0.58	0.150
Grain mixtures	-0.64	0.66	0.17	1.02	0.920
Fruit excluding juice	-0.48*	0.20	-0.61**	0.27	0.266
Fruit juices	0.34	0.25	0.18	0.46	0.429
Potatoes	-0.50	0.29	-0.87**	0.41	0.333
Other vegetables	-0.41*	0.19	-0.19	0.29	0.057
Fats	-0.14	0.08	-0.34***	0.11	0.031
Oils	-0.26	0.15	-0.52**	0.20	0.094

Notes: See Table 3.

Table A4: Moderate Depression (PHQ $\geq$ 10): Percentage of Calories Consumed

			Lewbel's Approach		
	PHQ	S.E.	PHQ	S.E.	J test p-value
	(1)	(2)	(3)	(4)	(5)
Percent Inferior (Aggregate)	3.26***	0.38	4.56***	0.81	0.207
Inferior Goods					
Creams	0.31***	0.07	0.59***	0.19	0.481
Milk desserts and sauces	0.18	0.14	0.21	0.26	0.602
Cheeses	-0.06	0.12	-0.03	0.22	0.388
Dry beans, legumes, and nuts	0.02	0.19	0.44	0.33	0.901
Sugars and sweets	0.72***	0.15	0.94***	0.30	0.744
Coffee and tea	0.29**	0.13	0.56**	0.26	0.533
Soft drinks, carbonated	1.64***	0.20	1.88***	0.51	0.681
Alcoholic beverages	-0.06	0.25	-0.11	0.41	0.193
Water	-0.01	0.02	-0.03	0.03	0.118
Normal Goods					
Milks and milk drinks	0.16	0.18	0.05	0.31	0.399
Meats	-0.48	0.28	-0.79*	0.43	0.842
Sausages, lunchmeats, and organ meats	-0.19	0.13	-0.41*	0.23	0.641
Fish and shellfish	-0.01	0.15	0.22	0.32	0.906
Meat in mixtures	0.09	0.38	-0.14	0.63	0.548
Eggs	-0.27	0.15	-0.44	0.26	0.677
Breads, crackers, and snacks from grain	-0.53	0.30	-0.62	0.50	0.732
Cakes, pastries, and other grain products	-0.29	0.26	-0.51	0.43	0.141
Pasta and cereal	-0.08	0.22	0.49	0.40	0.172
Grain mixtures	-0.45	0.45	0.24	0.71	0.911
Fruit excluding juice	-0.33*	0.14	-0.48**	0.20	0.292
Fruit juices	0.19	0.17	0.12	0.31	0.451
Potatoes	-0.34	0.19	-0.63**	0.29	0.351
Other vegetables	-0.27*	0.13	-0.12	0.20	0.069
Fats	-0.09	0.06	-0.27***	0.08	0.038
Oils	-0.18	0.10	-0.41**	0.14	0.101

Notes: See Table 3.

Table A5: Mild Depression (PHQ $\geq$ 5): Percentage of Calories Consumed

			Lewbel's Approach		
	PHQ	S.E.	PHQ	S.E.	J test p-value
	(1)	(2)	(3)	(4)	(5)
Percent Inferior (Aggregate)	2.15***	0.25	3.31***	1.02	0.168
Inferior Goods					
Creams	0.19***	0.05	0.43**	0.18	0.512
Milk desserts and sauces	0.09	0.10	0.18	0.22	0.648
Cheeses	-0.02	0.09	0.01	0.18	0.403
Dry beans, legumes, and nuts	0.04	0.14	0.37	0.29	0.932
Sugars and sweets	0.48***	0.11	0.69**	0.29	0.801
Coffee and tea	0.18*	0.10	0.44*	0.24	0.559
Soft drinks, carbonated	1.10***	0.15	1.51***	0.60	0.702
Alcoholic beverages	-0.02	0.19	-0.08	0.39	0.214
Water	-0.01	0.02	-0.02	0.03	0.126
Normal Goods					
Milks and milk drinks	0.11	0.13	0.12	0.29	0.422
Meats	-0.31	0.21	-0.62	0.41	0.867
Sausages, lunchmeats, and organ meats	-0.12	0.10	-0.32	0.21	0.658
Fish and shellfish	0.03	0.12	0.27	0.30	0.923
Meat in mixtures	0.06	0.29	-0.09	0.58	0.579
Eggs	-0.18	0.11	-0.36	0.24	0.694
Breads, crackers, and snacks from grain	-0.36	0.22	-0.49	0.47	0.754
Cakes, pastries, and other grain products	-0.21	0.19	-0.43	0.39	0.159
Pasta and cereal	-0.04	0.16	0.41	0.36	0.193
Grain mixtures	-0.32	0.35	0.29	0.66	0.918
Fruit excluding juice	-0.21*	0.11	-0.38**	0.18	0.318
Fruit juices	0.13	0.12	0.10	0.27	0.472
Potatoes	-0.22	0.14	-0.51*	0.28	0.377
Other vegetables	-0.18*	0.09	-0.08	0.17	0.081
Fats	-0.06	0.04	-0.21***	0.07	0.041
Oils	-0.12	0.08	-0.34**	0.13	0.114

Notes: See Table 3.