The Effect of Energy Price Shocks on Household Food Security

PRELIMINARY AND INCOMPLETE - DO NOT CITE

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Abstract

This paper examines how price shocks of energy resources including gasoline, natural gas, electricity and heating degree days affect three indicators of food insufficiency at a household level. Using the Current Population Survey-Food Security Supplement combined with energy price data from the Energy Information Administration and weather information from the National Oceanic and Atmospheric Administration, we find that positive price shocks in gas and natural gas increase the probability of food insecurity and food stress while negative price shocks of heating fuels decrease the probability each indicator of food stress. The most important effects occurred with negative heating fuel price shocks in the low income and cold state-residing low income subgroups. We also consider the effectiveness of federal assistance programs in cushioning households from price or weather shocks. We find that heating and food assistance are most effective in low income households that reside in cold states.

1 Introduction

There is considerable empirical evidence that households adjust the quantity and quality of foods they eat in response to unexpected increases in energy prices (Bhattacharya et al 2003; Cullen et al 2005; Gicheva et al 2010; Beatty et al 2011). Because no substitutes exist for energy in the short run, energy consumption is sticky. As a result, households may have little choice but to hold quantities roughly constant when faced with an unanticipated price change. While this trade-off is well documented, it isn't clear whether these shocks are large enough make households engage in behaviors consistent with food insecurity such as skipping meals, cutting the size of meals and/or lacking sufficient money to buy enough food for the household. Households may simply be able reallocate expenditure in such a way as to maintain food sufficiency. This paper investigates the link between exogenous shocks in energy prices and weather and household food security.

Because the demand for energy is inelastic, as prices increase households reallocate their income from other expenditure to energy to maintain a constant level of fuel consumption in the short run. Previous work found that household gasoline expenditure increased at the same rate as gasoline prices. In short, households behaved in a manner consistent with energy having an own price elasticity of zero. In the same vein, an unexpected drop in prices could increase disposable income, permitting households to allocate more money to other household expenditures at the margin. However, a drop in food expenditure is not equivalent to a drop in the quantity of food consumed. Aguiar and Hurst (2005) consider whether the fall in individual food expenditure that occurs after retirement directly translates to a drop in consumption. Using the Continuous Survey of Food Intake of Individuals (CSFII), they find that at retirement, expenditures fall by 17%, whereas time spent on food preparation and shopping increases by 53%. The drop in expenditure does not necessarily translate into individuals eating less or eating poorer quality food. In this paper, we examine whether shocks in prices of gasoline, natural gas, electricity and weather are large enough to push households into or out of food insecurity. We will examine three progressively more severe indicators of food insufficiency in order to understand the full effect of energy price shocks on households' self-assessed ability to afford and access sufficient food.

This paper stands at the intersection of two complementary fields of research: (1)the "heat or eat" literature which examines how weather and energy price shocks affects food expenditure and (2) the food security literature which explores the determinants of food security. This is the first study to examine the question of whether a household's response to exogenous price shocks is large enough to affect food stress and food security status.

The "Heat or Eat" question has been the focus of a number of studies. Results consistently show that households at low levels of income or expenditure are likely to adjust food expenditures in response to price and weather shocks.[1] Both food and fuel expenditures take up a greater share of low income households' budgets compared to middle and high income families. Furthermore, low income households have minimal financial buffers to protect themselves from unexpected price increases (Carroll 2011). Bhattacharya et. al. (2003) link the Consumer Expenditure Survey (CES) and National Health and Nutrition Examination Survey (NHANES) to temperature data from National Oceanic Atmospheric Administration (NOAA). They observe that in all levels of income, families increase their fuel expenditure in response to unexpected cold spells. However, only low income families reduce food expenditure when cold weather shocks occur[2]. The observed reduction in food expenditure is similar to the observed increase in fuel expenditure, implying low income families give up food in order to pay for heat. Two studies have further discussed the relationship between heating costs and household expenditure. Cullen, Friedberg and Wolfram (2005) focus on the difference between anticipated and unanticipated shocks and find expected price or weather changes have no effect on households at all levels of income, implying most households have the means to smooth consumption when

[1] Beatty, Blow and Crossley (2011) show that energy price and temperature shocks can be thought of as analogous, if households require a minimum level of heating.

[2] Alternatively the results could be interpreted to mean that households increase food expenditure when temperatures are unseasonably warm, thereby reducing heating costs.

anticipated price changes occur. Conversely, unanticipated shocks greatly affect the expenditure of low income households. This suggests that unexpected shocks have more severe consequences when households lack sufficient financial means. Finally, Beatty, Blow and Crossley (2011) study a similar question in the United Kingdom and find, as with the previous studies, cold weather shocks cause households of all incomes to increase their fuel expenditure; but only low income households adjust their food expenditure when faced with large unexpected shocks.

The literature has found that gasoline price shocks also affect household expenditure. Gicheva et al (2010) examine how increases in gasoline prices affect food expenditure and find that households decrease food expenditure as gasoline prices increase. They find that consumers tend to substitute away from eating out and toward more affordable grocery store consumption; furthermore, consumers tend to reallocate food expenditure toward sale items. As in previous work, the response is largest for low income households. In short, previous work has consistently found that exogenous energy price and weather shocks cause households to restrict spending on other goods, including food.

Recent literature on food security has focused on documenting the factors that contribute to food security status of a household. Many of these studies consider factors as employment, home ownership and income (Olson et. al. (1997), Rose (1999), Furness et al (2004)). Concerns about endogeneity make the conclusion of these studies problematic. As a means of addressing these shortcomings, Gundersen and Gruber (2001) and Leete and Bania (2009) study how deviations from expected income, not income itself, affect food security status. Gundersen and Gruber (2001) find that deviations from the household's mean income are more precise predictors of food consumption than household income. Although the authors do not consider the causal relationship between income deviations and food security, it does demonstrate a significant correlation between food insecure households and income shocks. Leete and Bania (2009) extend this approach by examining whether deviations from mean household income is associated with household food insecurity. They find that low income households with liquidity constraints are most susceptible to shocks and, as a result, at a greater risk for food insecurity. Likewise, as income level declines, income itself becomes less important in predicting food security than shocks to income. However, the extent to which the income shocks considered, such as job loss and separation, are truly exogenous to the household is an open question.

The "Heat or Eat" literature has found that exogenous energy price shocks and unexpected cold spells affect food expenditure, but do not establish whether the shocks are sufficiently large to create (or conversely relieve) hardship. As noted, the food security literature has found that low income households are unable to smooth large, potentially endogenous shocks. In this paper we build on both literatures to observe whether the small exogenous shocks associated with unanticipated changes in energy prices or temperatures–which have been shown to affect food expenditure–are large enough to increase the probability a household is classified as food insecure (or in the case of a negative price shock, decreases the probability a household is classified as food insecure). The paper proceeds as follows. Section 2 outlines a simple model of fuel price shocks and income effects. Section 3 discusses data sources and defines the dependent variables used as food stress and food insecurity indicators. Section 4 describes the empirical approach and estimation strategy to isolate the effect of prices shocks on food insufficiency indicators. Section 5 presents the results. Section 6 discusses the effects of social program participation. Section 7 presents a discussion of the results and 8 concludes.

2 A Model of Price Shocks

We propose a simple model linking energy price shocks to food insecurity. This model also applies to temperature shocks. To do this we show how the income effect of an unexpected energy price shock affects households that either lack sufficient liquid assets to smooth consumption or, in the case of lower than expected prices, relax a household's budget constraint. Note that previous work has found that a large percentage of low income households have zero liquid assets (Ageletos et al 2001) and at-risk households have little savings (Hurst and Ziliak, 2005; Lusardi et al 2011). When prices jump unexpectedly, these families have few resources to cope with price changes and must alter other household expenditure. When prices fall unexpectedly, low income households are likely to have a high marginal propensity to spend. Because energy is an inelastic good, the income effect from price shocks will be significant as the household maintains a relatively constant level of consumption. Because low income families tend to have limited or no assets and a high marginal propensity to spend, we assume that households only have access to within period income for food and fuel consumption.

Utility is defined over fuel h and food f where there is a critical level of food, f^*. Any f below f^* results in an insufficient quantity of food and, consequently, food insecurity. Suppose a household maximizes utility: $U(f,h)$ subject to its household budget constraint $m = p_f f + p_h h$. Because we are interested in how food security changes in response to price shocks, we totally differentiate food demand $f(p_f, p_h, m)$ to observe how the quantity of food demanded by the household changes,

$$df = \frac{\partial f}{\partial p_h} dp_h + \frac{\partial f}{\partial p_f} dp_f + \frac{\partial f}{\partial m} dm. \tag{1}$$

There is no change in food prices or income, $dp_f = dm = 0$, and therefore (1) simplifies to,

$$df = \frac{\partial f}{\partial p_h} dp_h. \tag{2}$$

In order to show how a price shock affects the quantity of food through the substitution and income effects, we write the Slutsky equation from the first order conditions of the utility function,

$$\frac{\partial f}{\partial p_h} = \frac{\partial f^u}{\partial p_h} - \frac{\partial f}{\partial m}\frac{\partial m}{\partial p_h}, \tag{3}$$

where $\frac{\partial m}{\partial p_h} = h$. In the short run, the term $\frac{\partial f^u}{\partial p_h}$ is very small given the limited substitution possibilities between food and fuel. Because of this, the dominating impact of the price shock comes from the income effect.

Substituting the income effect from the Slutsky equation into (2) we have,

$$df = -\frac{\partial f}{\partial m} h \times dp_h, \tag{4}$$

which shows the change in quantity of food as a result of the energy price shock.

From here we can show how the change in quantity of food affects the food security status of a household. Recall f^* is the critical level of food for the household. A household is food secure if $f > f^*$ or $f - f^* > 0$. In words, a household is food secure if the difference between what the household consumes and the critical level of food is greater than zero, or the household is consuming more than the critical level of food. After a price shock, the total quantity of food becomes $f + df$ where f is the household's initial quantity of food. Plugging (4) into the food security equation a household is food secure if,

$$f - \frac{\partial f}{\partial m} h \times dp_h - f^* > 0. \tag{5}$$

In this case, a change in the quantity of food caused by the income effect, $\frac{\partial f}{\partial m} h \times dp_h$ is not large enough to force the household's food consumption below f^*.

Figure 1 illustrates how price shocks affect whether a household is food secure. In the figure, an unexpected increase in fuel prices results in a drop in the quantity of food, and the household moves from point A to point B. Because point B is less than f^*, the household has insufficient food and is therefore classified as food insecure. Conversely, an unexpected drop in energy prices can lift households out of food insecurity. If a negative price shock occurs, the income effect yields a higher amount of disposable income and, as a result, the household is able to increase the amount of food it consumes. If the negative price shock is large enough, a food insecure household can increase its quantity of food to a level above f^* (i.e. from point B to point A), resulting in food security.

Because we have shown

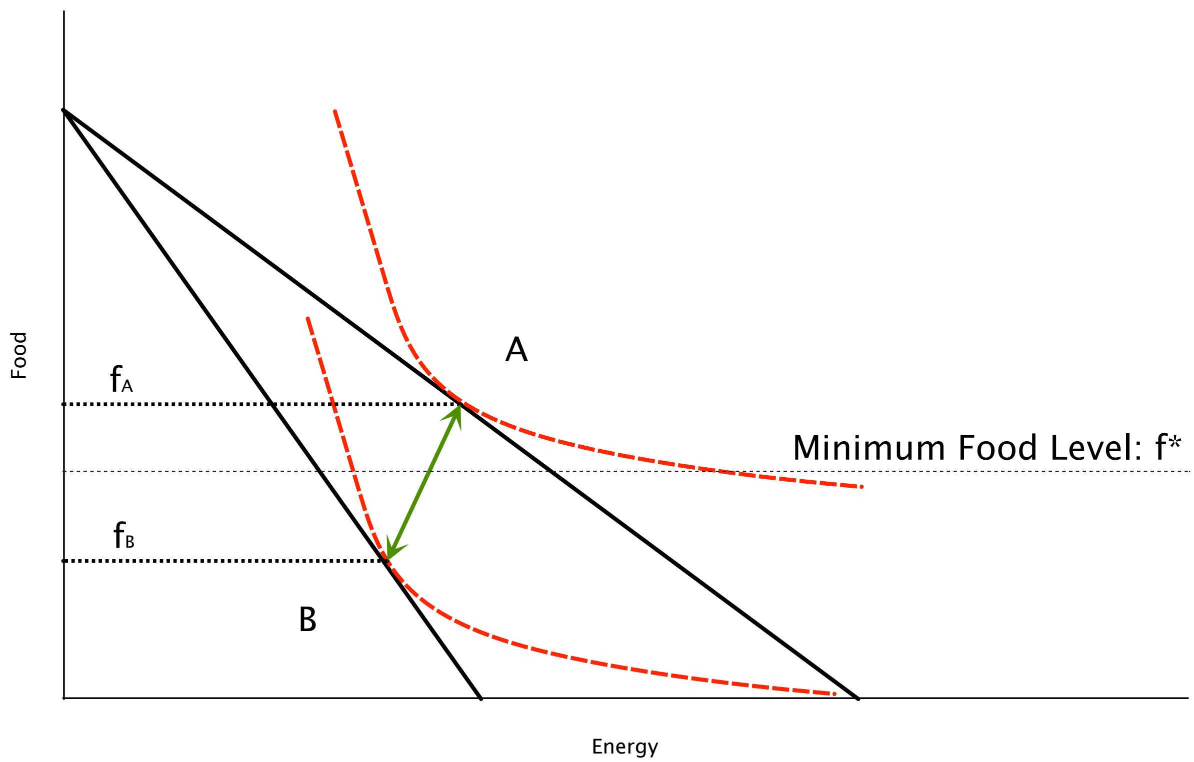
$$f - \frac{\partial f}{\partial m} h \times dp_h - f^* > 0, \tag{6}$$

translates to a household being classified as food secure, we can extend this equation to show

$$\begin{aligned} \Pr(\text{Food Secure} = 1) \quad &= \Pr(f + df - f^* > 0) \\ &= \Pr\left(f - f^* > \frac{\partial f}{\partial m} h \times dp_h\right), \end{aligned}$$

or the probability a household is food secure is equal to the probability a price shock is less than the difference between initial quantity of food and the critical level of food. Because food

Figure 1: Fuel Price Shocks and Food Insufficiency



security is a latent variable, we only observe whether an individual household is food secure or food insecure. Accordingly, we use a discrete choice model for the analysis.

3 Data

To examine food insufficiency and fuel price shocks, we combined the Current Population Survey-Food Security Supplement (CPS-FSS) with monthly energy price including gasoline, natural gas and electricity prices as well as Heating Degree Day (HDD) data that captures any unexpected cold spells. Heating Degree Day data will capture any unexpected drops in temperatures for each state. The CPS is a monthly survey of roughly 50,000 households from the non-institutionalized civilian population throughout the United States. The CPS collects information on employment, income, and demographic characteristics such as age, race and gender. The Food Security Supplement includes a number of questions on food access, expenditure, shopping and nutrition programs. It also includes a 12 item food security questionnaire used to classify a household as food secure or food insecure with in the past 30 days. These questions include whether the household cut the size of meals due to limited food, went hungry due to limited resources to buy food, or skipped meals due to limited resources and food as well as other questions regarding food access and consumption. From 2001 until 2009, the survey was administered during the month of December and in 2000, the survey was administered in September. Because the literature finds low income families are most responsive to price shocks and these families lack savings and credit to smooth consumption, we believe household's immediate experiences of and responses to price and weather shocks would be most informative. For this reason, we used the food security variable based on a thirty day reference period.

We obtain gasoline, natural gas and electricity price data from the US Energy Information Administration (EIA). Gasoline prices are reported as dollars per gallon of regular gasoline from each state in each month from years 2000 until 2009. Natural gas prices are reported as dollars per thousand cubic feed for residential consumer for each state in each month for the same time span. Finally, electricity prices are reported as cents per kilowatt hour from each state in each month. We obtain HDD data from the National Oceanic and Atmospheric Administration (NOAA) for each state in each month from 2000 until 2009. Heating Degree Days are estimates of how much a household resident must heat his or her home. HDD is estimated by subtracting the outside temperature from the base temperature of 65 degrees; these daily calculations are aggregated over the month. If the result is negative, or the outside temperature is greater than 65, the value for that specific day is zero.

The period of analysis takes place over the time period 2000 until 2009. We estimated the relationship between price shocks and the probability a household is food insecure by obtaining data on state-level gasoline, natural gas, and electricity prices from the EIA for each year and month as well as state-level HDD data for each year from NOAA. To create the data set, we merged energy price and temperature data using each household's state of residence and the year of the survey was conducted.[3]

We focus on three measures of food insufficiency that may capture increasing levels of hardship: a liquidity variable that captures whether or not the household states it needs more money in order to purchase enough food; a food stress variable that classifies different levels of a household's access to food which includes whether the household believes it accesses enough food and sufficient quality food; finally, the official USDA 30–day measure of food security. Each dependent variable was recoded as a zero–one variable where one signals food insecurity, food stress or the need for more money. The CPS-FSS variables and questions are included in Table 1.

The effects of a price or temperature shock will most likely affect different populations differently and, therefore, we expect to see a differentiated response. Because of this, we examine three separate populations: (1) the total population in the sample; (2) households at or under 185% of the Federal Poverty Guideline (FPG); (3) households at or under 185% of the FPG who reside in cold states. We define cold states simply as the 24 states with the coldest average temperature for each survey month. Previous literature has found that low income households tend to have a greater response to price and weather shocks as well as a greater likelihood to adjust food expenditure as a result of price shocks (Cullen et. al. 2004). Because of this, it seems plausible that households in cold states will have the largest response to heating fuel price shocks.

[3]Because the analysis is of household food security and not individual food insecurity, we used household heads as a unit of analysis to prevent double-counting of food security and demographic information from a single household.

Table 1: Dependent Variables

Variable	Variable Name	CPS-FSS Question
HRFS30D1 or HRFS30M1	Food Insecure	Based on the number of affirmative responses to 12 item 30 Day Food Security Questionnaire
HESS1	Food Stress	"Which of these statements best describes the food eaten in your household: enough of the kinds of food we want to eat, enough but not always the kinds of food we want to eat, sometimes not enough to eat, or often not enough to eat?"
HES8B or HES10	More Money	"In order to buy just enough food to meet your needs or the needs of your household, would you need to spend more than you do now, or could you spend less?"

To be classified as food insecure, households must indicate behavior including cutting sizes of meals, skipping meals and feeling hungry. Indicators *food stress* and *more money* are less severe measures of food insufficiency. Figure 2 illustrates the proportion of the sample that suffers from food insecurity, food stress or needing money over the time period of analysis. All indicators have a large range of values, showing variation over the sample period. At the same time, these indicators follow a similar pattern, dropping in 2001 and spiking around 2005 through 2007. Table 2 shows the summary statistics of the population, indicating the overall rate of the three food insufficiency indictors as well as the general demographic characteristics of the sample. Note that the low income subgroup has higher rates of each food insufficiency indicator, nearly double that of the total population subgroup.

Table 2: Summary statistics

	Total Population n=377,707		**Low Income Population** n=124,664		**Low Income - Cold State** n=58,386	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Food Insecure	0.052	0.221	0.117	0.321	0.115	0.318
Food Stress	0.218	0.413	0.388	0.487	0.369	0.483
More Money	0.117	0.321	0.228	0.419	0.211	0.408
Age	48.658	16.524	49.446	19.439	49.808	19.842
White	0.868	0.338	0.808	0.394	0.87	0.336
Black	0.087	0.281	0.138	0.345	0.076	0.265
Am Indian	0.01	0.101	0.019	0.135	0.021	0.143
Asian	0.025	0.156	0.022	0.148	0.02	0.141
Other Race	0.01	0.1	0.013	0.114	0.012	0.111
Female	0.474	0.499	0.575	0.494	0.571	0.495
Married	0.546	0.498	0.383	0.486	0.369	0.482
Employed	0.668	0.471	0.47	0.499	0.477	0.499
WIC Part	0.028	0.165	0.08	0.271	0.076	0.265
Total HH Number	1.843	0.586	1.831	0.686	1.798	0.686
Number of Children in HH	0.614	1.019	0.758	1.187	0.729	1.182

4 Empirical Approach

The empirical strategy is to analyze the effect of unexpected price changes on three separate binary dependent variables that indicate varying degrees of food insufficiency. Following Angrist and Pischke (2009), we estimate separate linear probability models (LPM) for each food insufficiency variable.[4] The analysis includes household, energy price and HDD data from the continental 48 states over ten years with one energy price and HDD observation per state for each year. Because the CPS–FSS is only administered one month out of each year, we only use energy price and HDD shock data for the month of the survey yielding 480 independent observations on energy prices and weather shocks. To be complete, we estimated the identical model with shock data for the month prior to the survey; this yielded similar results.

As noted, previous work has found households show a greater response to unanticipated prices changes than those that are anticipated. Therefore, we define a price shock for each energy type and for heating degree days to be a large deviation from expected prices or temperatures. In order to construct these shocks, we ran the following regression

$$Price_s = Trend_t\beta_1 + Trend_t^2\beta_2 + v_s + e_st \tag{7}$$

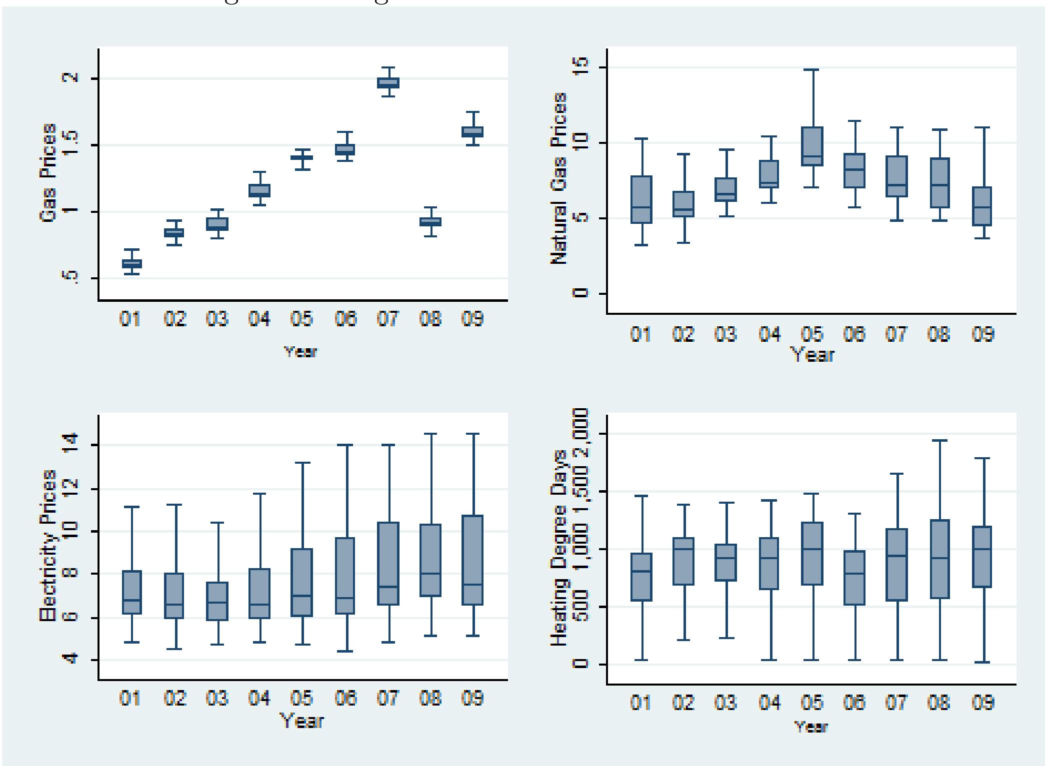
where $Price_s$ is state level monthly energy prices or HDD, $Trend_t$ is the difference between the current year and 1999, and v_s is a state fixed effect. We treat deviations from fitted values (i.e. the residuals, e_st) as shocks. These residuals capture deviations from the expected fuel price based on the information set available to the household at every point in time.

From here, we standardized these shock variables and created dummy variables equal to one if the shock was one deviation away from the expected price. Because positive and negative shocks may have opposite and not necessarily symmetric effects, we included separate dummies for shocks one standard deviation above and below the expected price.[5]

[4]Using LPM for analysis is associated with two specific problems: estimated probabilities are not constrained between zero and one and the error term is heteroskedastic. Despite these drawbacks, a number of researchers testify to the reliability and ease of LPM (Heckman and Snyder 1997, Falk, Lalive, Zweimller 2004, Rosenthal 1989).

[5]The choice of a one standard deviation cut-off is a natural one, but is admittedly ad hoc. On this basis roughly 16% of month/state price observations will be classified as positive shocks, roughly 16% will be classified as negative shocks and roughly 68% of price observations will serve as the control periods.

Figure 2: Exogenous Variables Variation Over Time



As Figure 3 illustrates, average prices remain fairly consistent for heating fuels, as do heating degree days but deviations are large. But gasoline prices are more volatile although the range is relatively small, indicating that gasoline prices vary relatively little between states. On the other hand, electricity, natural gas prices and heating degree days vary much more by state. For example, in 2008 natural gas prices ranged from around \$6 in North Dakota to above \$14 in Florida, implying that state level characteristics may affect heating fuel prices.

For this analysis, our empirical model for price and weather shocks is

$$Prob(FI_ist) = Shock_s(+)\beta_1 + Shock_s(-)\beta_2 + X_i\beta_3 + u_t + v_s + e_st \tag{8}$$

where FI_ist is our outcome variable, $shock_s$ are positive and negative price and weather shocks, X_i are household demographic variables which include household number, gender, race, income dummies, and whether a member of the household receives WIC. In the CPS, income is reported as a categorical variable and include sixteen dummy variables to capture category membership. Because we assume unobservable state and year factors influence price shocks and different indicators of food insufficiency, we include state and year-level fixed effects and cluster standard errors at the state level to control for arbitrary within state correlation where u_s are state–level fixed effects and v_t are year fixed effects. Because electricity price, natural gas price and HDD shocks may be related, we run a final regression including all energy price and weather shocks in order to observe if omitted variables affect our results.

We run all price shock and weather shock regressions on the total population and low income population. For the low income population that resides in cold states, we run only electricity, natural gas and HDD shock regressions. This is because we assume gasoline price shocks will not affect the probability of food insufficiency differently in cold or non–cold states. As previously mentioned, we estimate these regressions using LPM.

5 Results

Because energy prices are price inelastic, the hypothesis is that the probability a household suffers from some level of food insufficiency will increase in response to positive price or heating degree day shocks and decline in response to negative shocks. We expect the effect will be largest for low income families. Because of the clear hypothesis from theory, to test the significance of the key variables of interest, we use the natural one-sided test for each price and weather shock variable. In the interest of space we do not report coefficient estimates of individual household characteristics. The results are shown in Tables 3 through 7 at the end of this paper.

Table 3 and 4 show the results of the four separate regressions for the total population.

Gasoline price shocks, shown in Table 3, have little effect on the probability of $foodinsecurity$, $foodstress$, and *moremoney*. Although the signs are consistent with the theory, an increase in gasoline prices will decrease disposable income and therefore decrease ability to access sufficient food, positive shocks are not statistically significant in increasing the probability of food security, food stress, or needing more money. However, a negative price shock does show a statistically significant effect on the probability of food security which implies that negative price shocks can ease factors that contribute to households behavior consistent with food insecurity.

Food security variables are more responsive to heating fuel price shocks in the total population shown in Table 4. A positive price shock in natural gas increases a household's probability of being food insecure at a five percent significance level, but there is no significant effect on food stress or need for more money. A negative shock in natural gas has no effect on the probability of any food insufficiency indicator. A negative shock in electricity leads to a decrease in the probability of food stress but a positive shock has no effect. A positive shock in heating degree days, which implies an unexpected drop in temperature, has no effect on the probability of food insecurity, food stress or needing more money. But negative heating degree day shocks do decrease the probability of food stress. Combining natural gas, electricity and heating degree day shocks shows similar results to the separate regressions.

Table 5 and 6 report results from only the population at or below 185% of the federal poverty guideline. Previous work and theory suggests low income households are more responsive to income shocks and therefore we expect larger results from this population. For gasoline prices, a positive price shock increases the probability of food insecurity and food stress but does not increase the probability of a need for more money for food. A negative shock to gasoline prices decreases probability of food security at the one percent level, possibly implying an increase in disposable income and an increase in the ability to consume more goods. A positive shock in natural gas prices increases the probability of food insecurity but affects no other indicator. Similarly, a negative shock in natural gas prices result in a statistically significant decline in the probability of food insecurity but affects no other indicators. Positive price shocks to electricity do not affect the household, but negative price shocks decrease the probability of food stress and needing more money for food.. As in the total population, positive heating degree day shocks have no significant effect on food security, food stress or needing more food. Likewise, a negative shock to heating degree days results in no effect on the probability of all food insufficiency indicators.

Table 7 reports results from the most vulnerable population, low income households in cold states. Note that heating degree day shocks were not including in this analysis due to collinearity in the preliminary estimation. This population shows no response to positive price shocks. This result could suggest that households are already spending the minimum amount on food and fuel to sustain themselves and therefore cannot adjust when prices unexpectedly increase. Nevertheless, negative price shocks to electricity cause a reduction in the probability of food stress at a one percent significance level. Overall, negative price shocks decrease households self-assessed ability to access food. It is possible that because disposable income increases with unexpected negative price drops, money is reallocated toward food, lifting households out of food insecurity at the margin.

6 Discussion

Energy price shocks occur throughout the time period 2000 through 2009. The results have shown that when a positive price shock occurs, households repeatedly report feeling more food stressed or engaging in behavior that is consistent with food insecurity. On the other hand, the probability the household reports food stress or are classified as food insecure drops when negative price shocks occur. For the analysis, we considered positive and negative price shocks that were one standard deviation from the expected price shock. When interpreting the results, we calculated the average price shock one standard deviation from the expected price in order to understand the magnitude of price changes households faced.

Previous work found that positive gas price shocks can cause households to limit food consumption or expenditure. In low income populations constrained by limited savings and who spend a higher share of income on gasoline and food, a positive gasoline shock can prevent households from accessing sufficient food. Over the period of analysis, the average gasoline price shock was $0.45. In the poor population, we found that an increase in gasoline price by this magnitude increased the probability of food insecurity by 3% and food stress by 4%. There was no response in the total population; this confirms previous findings that poor populations are more vulnerable to unexpected price changes.

Unlike gasoline price shocks, heating fuel price shocks affected each subgroup in the analysis.

A positive natural gas price shock of \$2.37, the average price shock one standard deviation from the expected price, results in a 0.4% increase in the probability of food insecurity in the total population subgroup and a 1% increase in the probability of food insecurity in the low income population subgroup. Meanwhile, the average negative price shock for this fuel, \$2.20, is associated with a 1% reduction in the probability of food insecurity in the low income population subgroup. For the total population subgroup, negative price shocks had no effect on the probability of food insecurity.

The average positive price shock for electricity was \$1.37 but this did not increase the probability of any food insufficiency indicator. However, a drop in electricity prices of \$1.18 reduced the likelihood of food stress in the total population subgroup by 1.4% and needing more money by 1.2%. A negative price shock for electricity reduced the probability of food stress in the low income population by 1%. Negative heating degree shocks had no effect on the probability of any food insufficiency indicator in the total population, but a negative heating degree day shock was associated with a 1% drop in the probability of food stress. This is consistent with previous literature that found low income populations are more responsive to price and weather shocks than non-poor populations.

The most vulnerable population with the smallest sample size, low income households that reside in cold states, responded only to negative price shocks in electricity. Natural gas price shocks had no effect on the probability of food any food insufficiency indicators. A negative price shock in electricity, however, resulted in a 2.5% drop in the probability of food stress.

Negative price shocks seem to have the greatest impact on household food insufficiency. The statistically significant reduction in the probability of food insecurity as a result of negative shocks could imply that low income families, particularly those living in cold states, are already engaged in behavior consistent with food insufficiency. Only when there is an unexpected drop in price are households able to afford sufficient food. Consequently, the probability of food insufficiency decreases as price drops.

7 Conclusion

In this study, we found price shocks have a statistically significant effect on the probability of household food insufficiency indicators occurring, but the effect we found is small. Unexpectedly, positive price shocks seem to have a less consistent effect on food stress indicators suggesting that low income families are able to cope when positive price shocks occur. At the same time, we found that a fall in energy prices can directly effect household behavior related to food, and can decrease the probability of food stress. This may imply households are able to consume more or higher quality food.

This study is limited by the minimal amount of variation of energy prices in the data. This may be affecting the precision of the estimation. Due to this limitation, future research that includes longer time periods of analysis that can capture greater variation in energy prices either using more detailed geographic data or a longer time series.

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Table 3: Total Population

VARIABLES	(1) Food Insecurity	(2) Food Stress	(3) More Money
Gas Shock (+)	0.003	0.009	0.007
	(0.010)	(0.019)	(0.024)
Gas Shock (-)	-0.005***	-0.001	-0.001
	(0.002)	(0.003)	(0.003)
Observations	341,885	375,401	373,859
R-squared	0.076	0.133	0.096
States	48	48	48

Note: Regressions included state and year fixed effects, race, gender, employment,marital status, income, WIC participation, number in household, number of children

Robust standard errors in parentheses

One-Tailed test: *** p<0.01, ** p<0.05, * p<0.1

Table 4: Total Population

VARIABLES	(1) Food Insecurity	(2) Food Stress	(3) More Money	(4) Food Insecurity	(5) Food Stress	(6) More Money	(7) Food Insecurity	(8) Food Stress	(9) More Money	(10) Food Insecurity	(11) Food Stress	(12) More Money
Nat Gas Shock (+)	0.004**	0.002	-0.002							0.004**	0.001	-0.003
	(0.002)	(0.004)	(0.003)							(0.002)	(0.004)	(0.003)
Nat Gas Shock (-)	-0.003	-0.002	-0.018							-0.004*	-0.003	-0.003
	(0.002)	(0.003)	(0.002)							(0.002)	(0.003)	(0.002)
Elec Shock (+)				0.001	-0.001	0.003				0.001	-0.001	0.003
				(0.002)	(0.004)	(0.003)				(0.001)	(0.004)	(0.003)
Elec Shock (-)				0.000	-0.010***	-0.003				-0.004	-0.010**	-0.004*
				(0.002)	(0.004)	(0.003)				(0.002)	(0.004)	(0.003)
Heat Shock (+)							-0.005	-0.004	-0.0015	-0.004	-0.0007	-0.002
							(0.002)	(0.0010)	(0.0025)	(0.009)	(0.004)	(0.002)
Heat Shock (+)							-0.002	-0.010**	-0.001	-0.001	-0.010**	-0.001
							(0.002)	(0.004)	(0.0025)	(0.001)	(0.004)	(0.002)
Note: Regressions included state and year fixed effects, race, gender, employment,marital status, income, WIC participation, number in household, number of children												
Observations	341,855	375,401	373,859	341,855	375,401	373,859	341,855	375,401	373,859	341,855	375,401	373,859
R-squared	0.077	0.131	0.023	0.077	0.043	0.094	0.076	0.1352	0.0955	0.077	0.131	0.0961
States	48	48	48	48	48	48	48	48	48			

Robust standard errors in parentheses
One-Tailed test: *** p<0.01, ** p<0.05, * p<0.1

Table 5: Low Income Population

VARIABLES	(1) Food Insecurity	(2) Food Stress	(3) More Money
Gas Shock (+)	0.027*	0.037*	0.040
	(0.018)	(0.022)	(0.036)
Gas Shock (-)	-0.017***	-0.011	0.009
	(0.004)	(0.011)	(0.004)
Observations	111,952	124,447	123,520
R-squared	0.043	0.061	0.049
States	48	48	48

Note: Regressions included state and year fixed effects, race, gender, employment,marital status, income, WIC participation, number in household, number of children

Robust standard errors in parentheses
One-Tailed test: *** p<0.01, ** p<0.05, * p<0.1

Table 6: Low Income Population

VARIABLES	(1) Food Insecurity	(2) Food Stress	(3) More Money	(4) Food Insecurity	(5) Food Stress	(6) More Money	(7) Food Insecurity	(8) Food Stress	(9) More Money	(10) Food Insecurity	(11) Food Stress	(12) More Money
Nat Gas Shock (+)	0.011*	0.007	0.002							0.012*	0.006	-0.004
	(0.006)	(0.008)	(0.006)							(0.006)	(0.009)	(0.007)
Nat Gas Shock (-)	-0.009*	-0.07	-0.003							-0.008*	0.009	-0.004
	(0.005)	(0.005)	(0.004)							(0.005)	(0.005)	(0.004)
Elec Shock (+)				0.002	-0.006	-0.001				0.002	-0.007	-0.001
				(0.004)	(0.007)	(0.007)				(0.004)	(0.007)	(0.007)
Elec Shock (-)				-0.004	-0.014**	-0.012**				-0.002	-0.015*	-0.013**
				(0.004)	(0.006)	(0.006)				(0.006)	(0.006)	(0.006)
Heat Shock (+)							-0.012	-0.003	-0.002	-0.012	-0.005	-0.007
							(0.005)	(0.008)	(0.006)	(0.005)	(0.009)	(0.008)
Heat Shock (-)							-0.0013	-0.009	-0.006	-0.001	-0.007	-0.006
							(0.002)	(0.007)	(0.005)	(0.002)	(0.007)	(0.005)
Note: Regressions included state and year fixed effects, race, gender, employment,marital status, income, WIC participation, number in household, number of children												
Observations	111,952	123,788	123,100	111,952	123,788	123,100	111,952	123,788	123,100	111,952	123,788	123,100
R-squared	0.044	0.061	0.049	0.044	0.061	0.049	0.043	0.0612	0.0497	0.0439	0.055	0.044
States	48	48	48	48	48	48	48	48	48	48	48	48

Robust standard errors in parentheses
One-tailed test: *** p<0.01, ** p<0.05, * p<0.1

Table 7: Low Income Population Residing in Cold States

VARIABLES	(1) Food Food Insecurity	(2) Food Stress	(3) More Money	(4) Food Insecurity	(5) Food Stress	(6) More Money	(7) Food Insecurity	(8) Food Stress	(9) More Money
Nat Gas Shock (+)	0.005	0.004	0.002				0.005	0.003	0.0003
	(0.004)	(0.017)	(0.004)				(0.007)	(0.007)	(0.005)
Nat Gas Shock (-)	0.056	0.020	-0.003				0.007	-0.005	-0.007
	(0.006)	(0.008)	(0.008)				(0.006)	(0.007)	(0.009)
Elec Shock (+)				0.001	-0.004	0.005	0.002	-0.005	0.005
				(0.006)	(0.014)	(0.008)	(0.006)	(0.013)	(0.008)
Elec Shock (-)				-0.003	-0.025***	-0.010	-0.005	-0.024***	-0.011
				(0.005)	(0.009)	(0.007)	(0.004)	(0.008)	(0.008)
Note: Regressions included state and year fixed effects, race, gender, employment,marital status, income, WIC participation, number in household, and number of children									
Observations	51,977	57,441	57,097	51,977	57,441	57,097	51,977	57,441	57,097
R-squared	0.047	0.064	0.047	0.047	0.064	0.047	0.047	0.064	0.047
States	24	24	24	24	24	24	24	24	24

Robust standard errors in parentheses
One-tailed test: *** p<0.01, ** p<0.05, * p<0.1