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Do Households Smooth Small Consumption Shocks? Evidence from Anticipated and Unanticipated Variation in Home Energy Costs

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DO HOUSEHOLDS SMOOTH SMALL CONSUMPTION SHOCKS? EVIDENCE FROM ANTICIPATED AND UNANTICIPATED VARIATION IN HOME ENERGY COSTS[•]

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Home energy costs comprise a significant fraction of household budgets, particularly for poor families. This paper analyzes how household consumption responds to changes in home energy outlays over the course of the year. We specify Euler equations describing nondurable and food consumption and then rely on changes in energy prices and weather severity to identify exogenous changes in disposable income. We distinguish changes in energy spending that are anticipated, for instance because it is winter in the Northeast, from those that are unanticipated, for instance because it is an unusually cold winter. We find little evidence of excess sensitivity to anticipated variation among households in the Consumer Expenditure Survey 1990-2002, even among those without substantial financial assets. However, the latter group experiences large consumption reactions to unanticipated changes.

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1. Introduction

Home energy costs comprise a significant fraction of household budgets, particularly for poor families.[1] Moreover, home energy costs fluctuate both predictably and unpredictably with energy prices and seasonal effects. We exploit these sources of exogenous variation in disposable income for two purposes. One is to test the extent to which household responses to anticipated and unanticipated variation in home energy costs obey the predictions of consumption theory. The other is to analyze how poor households cope with variation in home energy costs and, if they are unable to buffer such costs, the degree to which spending on necessities like food and medical care suffers.

The first purpose of our paper complements other recent studies of anticipated changes in household resources. Some studies have found excess sensitivity of household expenditures to anticipated changes, in violation of the life cycle/permanent income hypothesis (dubbed the LC/PIH in some studies), while others have not. We extend this literature in several ways. First, we focus on a new source of variation in anticipated household resources. Variation in home energy costs affects a greater number and variety of households than the variation that many of the other studies have incorporated. Second, we focus on unanticipated as well as anticipated sources of variation, thus allowing a test of the precautionary savings motive as well as excess sensitivity. The relationship between any excess response to anticipated and unanticipated variation will provide a sense of the magnitude of possible sources for the violation. Third, the anticipated variation in home energy costs arising from seasonal effects, one of the sources we study, is likely to be salient, in the sense that most households should be aware of its occurrence. This will afford new evidence about the impact of saliency on tests of excess sensitivity.

The second purpose of our paper is to determine specifically how poor households adjust to variation in home energy costs. Both indirect and anecdotal evidence suggest that poor households hit by large increases in their energy bills are forced to cut back on spending for other essential goods and services. The possibility that some households must decide whether to "heat or eat" gained considerable attention in the media following sharp increases in fuel prices during the winters of 2000 and 2001.[2] A survey of poor families in Iowa where natural gas bills more than doubled reported that, "More than one in five ... went without medical care to pay for heating bills," and that, "Over 12% ... went without food to pay their home heating bill."[3] Public health studies suggest that poor children are more likely to be underweight during particularly cold winter months.[4] In the near future electricity deregulation is likely to expose households to greater price volatility and thus bigger swings in their non-energy disposable income.

Our identification strategy works as follows. We isolate exogenous changes in disposable income arising from variation in weather and energy prices among households using different

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[1] Home energy refers to energy used in the house, and excludes, most notably, gasoline expenditures.
[2] See, for example, "Price of Propane Making It Harder to Keep Warm", *The New York Times,* www.nytimes.com, February 5, 2001, and "Despite economic boom, millions are hungry", CNN, www.cnn.com, January 20, 2000.
[3] Mercier Associates (2000); also cited in *The Wall Street Journal*, April 6, 2001, "Study Shows 3.6 Million U.S. Families Face Prospect of Losing Energy Services." We contributed informally to this survey through discussions with Mark Wolfe, who heads the National Energy Assistance State Directors' Association.
[4] Frank et al. (1996).

types of fuel in different states, months, and years. Anticipated changes in disposable income arise from seasonal variation in weather and energy prices, while unanticipated changes arise from variation in the severity of a particular season and from energy price fluctuations. For example, we test for excess sensitivity to anticipated changes among households using different types of fuel and facing normal seasonal variation in fuel prices within Massachusetts and among households facing normal seasonal variation in temperature in Massachusetts versus Michigan. We test for consumption smoothing in response to unanticipated variation among households facing an unusually severe winter or unusually high heating oil prices in Massachusetts versus households facing typical electricity prices in Massachusetts or a typical winter in Michigan.

In principle, one could conduct this type of analysis using changes in expenditures for any good that is inelastically demanded and separable in utility from other consumption, but home energy spending is particularly well-suited due to the high variability of energy prices and needs. In addition, these expenditures account for a significant share of the typical household budget, so that the variation is economically meaningful. Finally, energy products are essentially commodities, so it is straightforward to identify the prices that households are likely to be facing.

We implement our analysis using data on household spending patterns in the Consumer Expenditure Survey (CEX) matched to monthly data on state-level energy prices and weather for the years 1990 to 2002. We follow previous studies that test the LC/PIH with household level consumption data and focus on nondurable expenditures and on food. We find little evidence of excess sensitivity to anticipated variation, even among those without substantial financial assets, but the latter experience large consumption reactions to unanticipated changes. Results from the analysis that focuses on low-income households will be incorporated in future drafts.

The rest of the paper proceeds as follows. Section 2 summarizes the related literature. Section 3 outlines our econometric framework and key identification assumptions. Sections 4 and 5 document patterns in home energy spending and state-level price and weather, respectively. Section 6 presents our first-stage estimates of the impact of energy prices and weather on energy expenditures and our second-stage estimates of the relationship between changes in energy costs and changes in spending in other categories. Section 7 concludes.

2. Related literature on the impact of income shocks

The relevant literature testing consumption-smoothing and the permanent income hypothesis can be divided into two main branches. First, many studies have focused on tests of excess sensitivity of household consumption to anticipated changes in resources. Examples include predictable changes in taxes or transfers, in household expenses, and in weather. Second, studies of consumption-smoothing test whether households can insure against unanticipated changes in resources, for example resulting from changes in employment, disability, or weather. While some of the studies focus on transitory income changes and some on permanent income changes, ours analyzes responses to both anticipated and unanticipated changes in transitory income.

2.1 Anticipated changes in resources

Since Hall (1978), researchers have tested the LC/PIH by estimating Euler equations and including a variable representing anticipated changes in income. Anticipated income changes should not alter consumption in the absence of liquidity constraints. Earlier researchers executed such tests by predicting anticipated income changes using past income and other observable variables, raising the problems that the household may know more than the researcher about future income and that the variables used to predict future income may affect the marginal utility of consumption as well.[5] Recent papers have offered innovative tests based on plausibly exogenous anticipated changes in household resources.[6]

Some of the recent papers find violations of the LC/PIH in the form of excess sensitivity to anticipated changes in resources. In studies focused on the timing of Social Security payroll tax payments (Parker 1999), income tax refunds (Souleles 1999), and the receipt of Social Security benefit checks (Stephens 2003), changes in nondurable and/or food expenditures coincide with predictable changes in these tax and transfer payments. Stephens (2004a) observes a similar outcome when households finish paying off their car loan at a predetermined time.[7]

However, the opposite result – that household expenditures are not altered when household resources change predictably – is found in studies of the receipt of a semiannual bonus to workers in Spain (Browning and Collado 2001), the receipt of annual payments to Alaskans (Hsieh 2003), the payment of college expenses (Souleles 2000), and the seasonality of income among Thai farmers (Paxson 1992a). Surprisingly, Hsieh shows that the same households that do not react to payments from Alaska's Permanent Fund do react to income tax refunds of the type Souleles (1999) studies.

A few general points about this body of research are important. First, the results often apply to restricted subsamples of the population, as a consequence of the type of variation utilized. Our approach allows us to focus on the broad set of households that face variation in home energy costs. Also, like only a few of the other studies, we observe the same household facing more than one change in disposable income and, moreover, facing both positive and negative changes.

Second, each of the studies invokes an exclusion restriction that justifies using a particular change in resources. In studies like ours involving changes in household expenses, a key identifying restriction takes the form of a separability assumption. For example, Souleles (2000) and Stephens (2004a) assume that the marginal utility of other consumption is separable from college choices and from car services, respectively.[8] As we discuss in more detail later, we assume separability of home energy expenses.

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[5] Browning and Lusardi (1996) and Attanasio (1999) summarize many of these earlier studies.

[6] Another innovation in recent studies has been the use of microdata rather than aggregate consumption data. Most of the studies of American data cited here use the quarterly interview survey of the CEX, as we do, although Stephens (2003) uses the CEX diary survey in order to capture daily consumption patterns.

[7] Stephens (2004b) finds evidence of excess sensitivity using a somewhat different approach. Rather than identifying an actual change in resources, he uses information on subjective job loss expectations as an indicator of an expected future change in resources. He documents that subjective expectations are informative about future outcomes and then that, among households experiencing job loss, prior expectations of job loss do not affect the magnitude of the subsequent decline in food consumption. Hence, households with information do not use it to smooth consumption. A problem with this study is the assumption of separability between food and leisure, which may be violated (Aguiar and Hurst 2004).

[8] Studies that do not rely on changes in expenses also involve some type of exclusion restriction. For example, differences in the timing and magnitude of Social Security payroll tax payments across households in the sample Parker (1999) studies are assumed to be uncorrelated with differences determining the time path of consumption.

Third, a few explanations have been offered to interpret the conflicting results. Evidence of the importance of liquidity constraints is mixed. Several, but not all, of the studies find a greater degree of excess sensitivity among low-wealth, low-income, and/or young households.[9] Stephens (2004a) observes such a relationship, but he also finds that excess sensitivity is not correlated with the length of the car loan, which is a direct indicator of liquidity constraints.

Alternative explanations suggest that optimization is imperfect because of effort and information costs. Browning and Crossley (2001) argue that households are more likely to smooth as the welfare loss from not doing so increases. Browning and Collado (2001) suggest that the semiannual bonus is better understood and larger – and hence more "salient", to use the terminology of behavioral economics – than the tax changes studied by Parker (1999) and Souleles (1999). Hsieh (2003) makes a similar argument to explain the differential responses to tax refunds versus payments from Alaska's Permanent Fund. Our seasonal weather changes may be more salient than seasonal energy price changes, which could afford new evidence about the relevance of saliency. On the other hand, the magnitude of the shocks we study are smaller than those analyzed by either Hsieh (2003) or Browning and Collado (2001), so our results provide new evidence on the determinants of saliency.

2.2 Unanticipated changes in resources

Some recent papers have focused on consumption responses to unexpected income shocks that are generally large and/or permanent. Several involve changes in household status – for example, from employed to unemployed, or from able-bodied to disabled. Such papers generally test whether consumption changes when the shock is experienced or whether the change in consumption is smaller than the change in income generated by the shock.

In general, households appear able to smooth consumption fairly well in response to moderate changes in income, but less well when the shocks are more severe (e.g. Gruber and Dynarski 1997, Gertler and Gruber 2002, Stephens 2001). Consumption-smoothing is facilitated by access to resources from both within and outside of the household – including depletion of household assets (the presence of which is attributed to self-insurance or precautionary saving), increased labor supply of other household members, transfers from other households, formal insurance holdings, and transfers from the government.

We view our approach as an informal test of a precautionary savings motive, since consuming out of buffer-stock savings may be the least costly way to insure against these relatively small transitory shocks.[10] In comparison, the employment and disability shocks that others study are often too big to be buffered solely by household assets. Public transfer programs and public and private insurance play an important role in mitigating some of those adverse income shocks (e.g. Gruber 1997 on unemployment insurance; Gruber 2000 on AFDC; Levy 2002 on private health

[9] For example, Souleles (1999) found that nondurable consumption of low-income households responded more to tax refunds in comparison to high-income households, but he found the opposite for durables. Parker (1999) found excess sensitivity among both low- and high-wealth households.

[10] Somewhat more direct tests of precautionary savings motives have been undertaken by determining whether households that face greater uncertainty save more, though it is difficult to find exogenous variation in the degree of uncertainty. A small body of research has undertaken the explicit estimation of a precautionary savings model, which requires numerical solution methods even with relatively simple forms of uncertainty.

insurance). While the federal Low Income Home Energy Assistance Program (LIHEAP) could in theory fill a similar function when poor households face swings in fuel costs, LIHEAP is in fact quite small, and assistance is routinely rationed.[11]

Compared to our approach, the difficulty with the studies that rely on changes in household circumstances is in disentangling changes in tastes for consumption and in expenditure needs precipitated by the shock from the direct effects of reduced income.[12] For instance, an unemployment spell affects not only income but also the marginal utility from consuming other goods. Unemployment may reduce the need to spend money on transportation and may induce a switch from consuming time-saving goods (such as pre-prepared food) to time-intensive goods (such as home-cooked food). Therefore, these studies are better able to address how individuals with the same income shock fare under different conditions (e.g. insured vs. uninsured) than how given individuals respond to exogenous income shocks holding preferences constant.

Another disadvantage is that longitudinal data on family characteristics are required to identify the change in household status. For this reason, a number of studies have relied on the Panel Study of Income Dynamics. A key advantage of the CEX is that it tracks virtually all categories of consumption and not only food. Disadvantages of the CEX are that it offers a much shorter panel and does not measure income as accurately. How well income is measured is much less of a concern for us because we do not rely on income variation for identification.

Lastly, it is important to discuss studies similar to ours that use weather-related variation. Paxson (1992) analyzes how variability in rainfall affects Thai farmers. She estimates the marginal propensity to save out of both transitory (unanticipated) and permanent (anticipated) income, predicting the latter with household characteristics. She finds that the propensity to save out of transitory income due to rainfall is high and that households save a significantly higher fraction of transitory than permanent income. In contrast, we consider only transitory changes in income and attempt to differentiate anticipated from unanticipated shocks. Also, we use repeated observations on households in the CEX, while her study is based on a cross-sectional survey.

The questions we study are broader and the approach we take more formal than a recent paper by Bhattacharya et al. (2003). They focus narrowly on the 'heat or eat' decision and, like us, estimate the impact of weather on food consumption using a sample of poor households from the CEX. They also study a separate survey on nutritional intake to explore the implications for diet and health outcomes. Since we also have the goal of testing predictions of consumption theory, we consider both broad and narrow categories of expenditures and distinguish between anticipated and unanticipated weather changes. We also include additional variation from energy prices and from information about individuals' energy needs and payment plans.

3. Empirical Approach

3.1 The Euler Equation

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[11] LIHEAP funding reached a high of $1.99 billion in fiscal year 2003.

[12] Gruber and Gertler (2002) argued that state dependence does not explain their results, since illness of non-working family members has only a small effect on consumption.

A household's Euler equation can be derived from the first-order conditions of the lifetime optimization problem facing a household with a risk-averse utility function and a lifetime budget constraint with no restrictions on borrowing.[13] Consider the following utility function, based on Lusardi (1996):

$$U(C_{i,s,t};Z_{i,s,t}) = \frac{1}{1-\gamma} C_{i,s,t}^{1-\gamma} e^{Z_{i,s,t} + \tilde{v}_{i,s,t}}$$

C is total nondurable spending over the last quarter for household i living in state s in month t.[14] γ is the coefficient of relative risk aversion. We assume that household tastes are shifted by an idiosyncratic preference shock $\tilde{\nu}$ and by household characteristics Z.

The household chooses the path of consumption to maximize the sum of lifetime utility discounted at rate δ, given the expected path of income and the interest rate r. The resulting first-order condition is the Euler equation:

$$U'(C_{i,s,t};Z_{i,s,t}) = \frac{1+r}{1+\delta} E_t\left[U'(C_{i,s,t+1};Z_{i,s,t+1})\right]$$
$$U'(C;Z) = C^{-\gamma} e^{Z+v}$$

Taking a log-linear approximation of the Euler equation, while subsuming the interest rate and discount rate in the constant term, yields the following:[15]

$$\Delta \ln\left(C_{i,s,t+1}\right) = \Delta Z_{i,s,t+1} + \nu_{i,s,t+1} \qquad (1)$$

$\Delta\ln(C_{i,s,t+1})$ is the percent change in total nondurable spending for household i from t to $t+1$. ΔZ are changes in household characteristics that predictably alter consumption growth, and $\nu = \Delta\ln(C_{i,s,t+1}) - E_t[\Delta\ln(C_{i,s,t+1})]$.

3.2 Testing the Life-Cycle/Permanent Income Hypothesis

The LC/PIH is often tested by adding a term to (1) so that

$$\Delta \ln\left(C_{i,s,t+1}\right) = \Delta Z_{i,s,t+1} + \beta^{ANT}\ \Delta E_t\left[\ln\left(X^{ANT}_{i,s,t+1}\right)\right] + \nu^{ANT}_{i,s,t+1}\ , \qquad (2)$$

while the consumption-smoothing tests described add a term to (1) so that

$$\Delta \ln\left(C_{i,s,t+1}\right) = \Delta Z_{i,s,t+1} + \beta^{UNANT}\ \Delta \ln\left(X^{UNANT}_{i,s,t+1}\right) + \nu^{UNANT}_{i,s,t+1}\ , \qquad (3)$$

where $\Delta E_t\left[\ln\left(X^{UNANT}_{i,s,t+1}\right)\right] = 0$.

[13] For recent discussions, see Browning and Lusardi (1996) and Attansio (1999). We ignore the possibility that the intrahousehold distribution of resources affects the household's spending decisions. We also assume separability of consumption over time and of nondurable consumption, durable consumption, and leisure. Our focus on home energy costs involves additional separability assumptions which we will address below.

[14] The time structure is slightly peculiar because the CEX interviews roughly one-third of its households in each calendar month (allowing us to include month effects and control for monthly weather and price variation later on) while collecting consumption data covering the prior three months.

[15] We ignore the second-order term involving the variance of expected future consumption, which drives precautionary savings behavior as a function of the degree of consumption risk a household faces.

In equation (2), $\Delta E_t[\ln(X^{ANT})]$ represents an *anticipated* change in household resources. An expected change should already be incorporated in consumption plans, according to the Euler equation, so β^{ANT} should equal zero if households do not face liquidity constraints. Following Hall (1978), researchers chose $\Delta E_t[\ln(X^{ANT})] = \Delta E_t[\ln(Y)]$, the anticipated change in household income, which was predicted using past income and other observable characteristics. More recently, $\Delta E_t[\ln(X^{ANT})]$ has involved some exogenous change in household resources, as discussed earlier.

In equation (3), $\Delta\ln(X^{UNANT})$ represents an *unanticipated* change in household resources. Examples of X^{UNANT} in the recent literature that we discussed in Section 2 include changes in earnings due to displacement or disability. Estimating the magnitude of β^{UNANT} represents an informal test of the degree of consumption-smoothing which a household can achieve.

We are interested in testing whether non-energy expenditures change when home energy costs change exogenously. Thus, we redefine our left-hand side variable as C^{NE}, expenditures exclusive of home energy costs, and choose $X^{ANT}=ENERGY^{ANT}$ and $X^{UNANT}=ENERGY^{UNANT}$ as sources of anticipated and unanticipated variation in household resources.[16] Estimating the effects of both on expenditures reveals whether consumption responds differently to anticipated and unanticipated energy spending. In addition to determining whether either coefficient is non-zero, we can consider whether $\beta^{UNANT}<\beta^{ANT}$, which would imply that households respond less to anticipated than unanticipated outlays.[17] In order to exploit these sources of variation, we must make some modifications to equations (2) and (3).

First, we have to account for the fact that home energy spending, unlike income, is not of the same order of magnitude as total expenditures and varies substantially within the sample. Home energy comprises about 5% of total expenditures for the median household in the full CEX sample, and this share ranges from 3% at the 25th percentile to 8% at the 75th. A given percentage increase in home energy outlays would translate into differing percentage reductions in disposable income across households, depending on their budget shares. Thus, the isoelastic assumption underlying the log specification of the Euler equation is inappropriate, and we choose a specification in levels instead.[18]

[16] To lay out the implications of this more formally, consider a utility function of the form:

$$U(C^{NE}_{i,s,t}, ENERGY_{i,s,t}; Z_{i,s,t}, Z^{E}_{i,s,t}) = \frac{1}{1-\gamma} C^{NE\ 1-\gamma}_{i,s,t} e^{Z_{i,s,t}+v_{i,s,t}} + f(ENERGY) \times e^{Z^{E}_{i,s,t}+v^{E}_{i,s,t}},$$

where f(.) is a concave function. Intertemporal optimization will yield separate Euler equations, one in C^{NE} and one in *ENERGY*, demonstrating that the planned change in C^{NE} (though not its level) is unaffected by the planned change in *ENERGY*. This formulation also makes it clear that, in the estimation, it will be important to assume that the disturbances $v_{i,s,t}$ and $v^{E}_{i,s,t}$ are uncorrelated conditional on all relevant covariates $Z_{i,s,t}$ and $Z^{E}_{i,s,t}$.

[17] Note that the a positive shock to *ENERGY* implies a negative shock to disposable income, so this is equivalent to considering whether $|\beta^{UNANT}|>|\beta^{ANT}|$.

[18] The linear specification can be derived either from a constant absolute risk aversion utility function or as a Taylor expansion around $C_{t+1}/C_t = 1$ of the log-linear Euler equation in (1). Souleles (1999, 2000) adopted a linear specification when he estimated the impact of tax refunds and of college costs, also relatively small in magnitude, on total household expenditures. Dynarski and Gruber (1997) did the same when studying the impact of income shocks on consumption.

Second, energy expenditures are influenced by other time-varying household characteristics that alter consumption choices. For instance, if a household member joins the labor force, both energy and other consumption might increase because household income goes up, or energy consumption might decrease because the house becomes unoccupied during the day. While we can control for changes in the number of earners,[19] there are likely to be other factors like these that are unobservable in our data that would cause *ENERGY* to be correlated with v.

These two concerns lead us to estimate a linear Euler equation and to use instrumental variables strategies to isolate exogenous variation in home energy costs. Given that we do not separately observe anticipated and unanticipated changes in energy, our underlying model is:

$$\Delta\left(C_{i,s,t+1}^{NE}\right) = \Delta Z_{i,s,t+1} + \beta^{k}\ \Delta\left(ENERGY_{i,s,t+1}\right) + v_{i,s,t+1}^{k} \tag{4}$$

$$\Delta\left(ENERGY_{i,s,t+1}\right) = g(\Delta W_{i,s,t+1}^{ANT}, \Delta P_{i,s,t+1}^{ANT}, \Delta W_{i,s,t+1}^{UNANT}, \Delta P_{i,s,t+1}^{UNANT}; \Delta Z_{i,s,t+1}, \omega) \tag{5}$$

Equation (4) is an augmented Euler equation, and equation (5) represents a first-stage relationship between changes in energy and our instruments. ΔW and ΔP represent vectors of anticipated and unanticipated weather and price changes.[20] We assume that, conditional on ΔZ, the weather and price variables are uncorrelated with v.

Then, in order to recover the separate effects β^{ANT} and β^{UNANT} of anticipated and unanticipated changes in energy outlays in equation (4), we run instrumental variables estimation twice. To obtain estimates of β^{ANT}, we instrument for Δ(*ENERGY*) in (4) using anticipated changes in weather and prices, and similarly to obtain estimates of β^{UNANT}, we instrument using unanticipated changes in weather and prices.[21] In some specifications, we expand the instrument set to include interactions between the weather and price variables, to allow energy price elasticities to vary as a function of weather.[22]

3.3 Identification assumptions

Our estimation strategy requires several identifying assumptions. First, and perhaps most importantly, home energy costs are assumed to be separable from other forms of consumption. If not, then even exogenous changes in energy costs would alter the marginal utility of consumption from other goods, so that the β's could not be interpreted as measuring reactions to changes in disposable income. This would be true if, for example, households buy sweaters or blankets or better insulation to conserve when it gets cold, or buy compact fluorescent bulbs to conserve when energy prices are high. Most of the purchases households might make to

[19] In fact, because of the way income and work status information is collected in the CEX, we can only convincingly identify *increases* in the number of earners between quarters, and this is the measure we include in our control set.
[20] This approach is similar to Paxson (1992b), who distinguishes unobservable permanent and transitory components of income. However, she notes that the variables she used to predict permanent income are likely to be correlated with the error term in her main savings equation, so she focuses on the variation used to predict transitory income.
[21] Note that one could explicitly decompose *ENERGY* into exogenous anticipated and unanticipated components as well as endogenous components that are correlated with v. Then, our approach is analogous to the IV solution to a classical measurement error problem, since we are only able to observe the composite change in energy outlays but are interested in the impact of the exogenous components.
[22] Archibald et al. (1982) find that price elasticities for residential electricity were higher during peak periods of demand (-0.47 during May, June, and July in the summer and November, December, and January in the winter) than in off-peak months (-0.27).

substitute for heating, cooling, or light are not in our definition of nondurables. We use the definition of "strictly nondurables" from Lusardi (1996) that excludes apparel, medical services, and education expenses from the NIPA definition, although we test robustness to using the NIPA definition. As long as credit markets are unconstrained, then spending on durables (including, in our definition, apparel and household equipment) would not contaminate the Euler equation.[23] We also presume that effects like these are likely to be small, since we find that home energy costs are quite inelastic to the shocks we examine.

Second, weather and energy prices must influence home energy costs in order for these to be valid instruments for changes in energy outlays. Our estimates of equation (5) demonstrate that this is the case, even after controlling for year and month effects. As we just mentioned, home energy demand is price- and weather-inelastic, implying expenditures rise significantly in response to the right-hand side variables.[24]

Third, energy price changes must *cause* home energy spending changes, and not vice versa, conditional on Z. If not, economic factors that shift energy spending and subsequently alter energy prices might also shift non-energy spending, leading to a correlation between energy prices and non-energy spending due to omitted variables.[25] However, since utilities are heavily regulated, prices do not respond contemporaneously to demand factors. Yet, to be cautious, we plan to remove any possible confounding effects of the business cycle by controlling for the unemployment rate and change in per capita income by state-month.

Fourth, weather and energy prices must not directly affect or be otherwise correlated with non-energy spending, conditional on Z. We take steps that involve the choice of control variables and the definition of the dependent variable to deal with potential omitted variables problems.

The most likely scenario under which non-energy spending would vary with weather is through seasonal patterns in consumption, if households eat different types of food or are differentially likely to eat out in the summer versus the winter. To address generic seasonality in consumption, we include month fixed effects in Z. More problematic for us is if households eat different types of food in the winter in different parts of the country, or if households eat different types of food when the winter is colder than average. We will address this in some specifications by including weather directly in the Euler equation (equation 4) and thus limiting our comparison to households facing similar weather but different fuel prices.[26]

The most likely spurious link between non-energy spending and energy prices is through a correlation between prices. Since gasoline price movements are correlated with home energy

[23] As we explain later, we use the definition of "strictly nondurables" from Lusardi (1996), which excludes apparel, medical services, and education expenses, as well as the NIPA definition. We exclude transportation spending from both, since gasoline price movements are correlated with energy price movements.
[24] Observations from households who sign up for time-of-use pricing uniformly suggest that own-price elasticities are less than one (e.g. Caves and Christensen, 1980). Using all customers (not just those on TOU meters) and variation in prices reflected in monthly bills, Reiss and White (2001) find that price elasticities are higher for households in the first income quartile.
[25] A similar assumption about energy spending changes not altering weather seems innocuous.
[26] Note that we cannot include state-month effects, since that would absorb all our weather variation (except when we interact weather with housing characteristics).

price movements, we exclude transportation expenditures from our definitions of non-durables.[27] We could alternatively control for changes in gasoline prices. We could control for general price movements as well, but we find at most small contemporaneous correlations between energy and other prices (besides gasoline) after controlling for month and year.

3.4 Implementing our estimation strategy

In order to execute our strategy, we first need to construct measures of anticipated and unanticipated weather and price changes. We use state-month observations, where the month references the three-month period *prior* to the current month (since the CEX interviews a rotation of households each month and asks them about their spending in the previous three months). Our weather variables are $W = \{HDD, CDD\}$, which are heating and cooling degree days summed over the previous three months. HDD and CDD measure the number of days with temperatures above or below baseline amounts and the severity of the temperature extremes on those days. Our price variables are $P = \{P^E, P^G, P^O\}$, which are electricity, natural gas, and home heating oil prices averaged over the previous three months (converted to 2000 dollars using the aggregate CPI). The price and weather data are described in more detail in Section 5 and in the data appendix.

We have data on normal heating and cooling degree days that we use as our measure of anticipated weather changes between quarters, ΔW^{UNANT}. We have tried two different approaches to predict anticipated price changes, ΔP^{ANT}, using either the average over the two prior years for the month in question or computing the average for the month over the entire sample period (excluding the year in question). We then compute $\Delta W^{UNANT} = \Delta W - \Delta W^{ANT}$ and $\Delta P^{UNANT} = \Delta P - \Delta P^{ANT}$. Thus, abnormal weather and price patterns are treated as surprises.

In theory, the anticipated and unanticipated components of weather and prices should be orthogonal; in practice, because the series are trending slightly and because of small sample issues, they are weakly correlated. At the moment we deal with the correlation between the anticipated and unanticipated series by including ΔW^{UNANT} and ΔP^{UNANT} as exogenous control variables in the Euler equation when we estimate the effect of $\Delta ENERGY^{ANT}$ on non-energy spending in (4), in order to eliminate omitted variable bias; and similarly, by including ΔW^{ANT} and ΔP^{ANT} in (4) when we estimate the effect of $\Delta ENERGY^{ANT}$. Also, in this draft we present the results only for the case where anticipated prices are computed from the state-month average over the sample period, since the results are qualitatively similar if we instead use the two-year moving average. In future drafts, we plan to develop more careful estimates of the anticipated and unanticipated variables that satisfy the orthogonality condition.

The remaining decision regarding estimation is choosing a functional form for the first-stage equation explaining changes in energy expenditures. If equation (5) is specified so that level changes in energy are related to level changes in prices and weather, then we can simply use our price and weather variables as instrumental variables to recover the coefficients of interest. As described above, we would instrument with ΔW^{ANT} and ΔP^{ANT} to estimate β^{ANT}, and we would instrument with ΔW^{UNANT} and ΔP^{UNANT} to estimate β^{UNANT}.

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[27] Alternatively, we could treat transportation, like energy spending, as providing exogenous variation in household resources. However, transportation services might be less likely to satisfy the necessary separability conditions.

We also use a more complicated alternative that may provide more precise estimates. We can specify equation (5) to match a more plausible energy demand function by relating changes in log energy expenditures to changes in log prices, as well as changes in weather. Thus, we estimate:[28]

$$\Delta\ln\left(ENERGY_{i,s,t+1}\right) = \phi^{WA}\Delta W^{ANT}_{s,t+1} + \phi^{PA}\Delta\ln P^{ANT}_{i,s,t+1} + \phi^{WU}\Delta W^{UNANT}_{s,t+1} + \phi^{PU}\Delta\ln P^{UNANT}_{i,s,t+1} + \phi^{Z}\Delta Z_{i,s,t+1} + \omega_{i,s,t+1} \quad (6)$$

Using the log-linear specification (6) requires a different estimation approach. We first estimate (6) using the full set of exogenous variables and predict $\Delta\ln(EN\hat{E}RGY)$, the change in log energy expenditures. We then instrument for the level change in energy expenditures $\Delta(ENERGY)$ in the Euler equation using this predicted value, $\Delta\ln(EN\hat{E}RGY)$.[29] Including the unanticipated weather and price changes in the Euler equation while instrumenting with the total predicted change in *ENERGY* isolates the effect of anticipated variation in this second step. Similarly, including the anticipated weather and price changes as control variables isolates the effect of unanticipated variation. Note that the standard errors from these IV estimations are not adjusted for the fact that the instrument itself is predicted.

In all cases we account for the fact that weather and energy prices vary only at the state/month level by adjusting the standard errors for clustering. Our control variables ΔZ that affect changes in consumption consist of household structure (change in household size and in the number of household members aged 0-2, 3-5, 6-18, and 65+); age (up to a quartic in the respondent's age); labor supply (change in the number of workers in the household); and time (month and year) dummies. Note that a household fixed effect in the level of consumption gets differenced out in the Euler equation.

In addition to including price and weather interactions in some specifications, we also estimate some that interact relevant instruments with information on whether a household pays energy bills on a predetermined payment plan or as part of their rent (so they do not face regular variation in their home energy costs), on the fuel that they use to heat their home, and on housing characteristics including whether they have air conditioning and the age, size and type (e.g., single-family, built before 1950).[30] The interaction terms augment the identifying variation from prices so that we can try including weather directly in the Euler equation.

[28] The linear specification estimated in the first stage of the 2SLS strategy outlined just above is the same, except that it does not take the logs of energy spending or prices.

[29] Note that we instrument for the endogenous regressor $\Delta ENERGY$ in the Euler equation with the predicted value $\Delta\ln(EN\hat{E}RGY)$ from (6) rather than running two-stage least squares (2SLS) after transforming $\Delta\ln(EN\hat{E}RGY)$ into a level change and replacing $\Delta ENERGY$. Running 2SLS with the transformed variable replacing the endogenous regressor yields inconsistent estimates (Hausman 1983). In addition, the predicted log change $\Delta\ln(EN\hat{E}RGY)$ is itself a valid instrument – it is correlated with the endogenous level-change $\Delta ENERGY$ and uncorrelated with the error term ν as long as the instruments are valid.

[30] To control for any confounding heterogeneity in consumption growth rates according to these characteristics, we include them as explanatory variables in the Euler equation.

Before turning to the estimates of the first-stage relationships of home energy costs and the IV estimates of the Euler equation, we discuss our household consumption data from the CEX and our weather and price data.

4. Home Energy Expenditures

We use data on home energy expenditures from the Consumer Expenditure Survey for households surveyed from the 2nd quarter of 1990 through the 1st quarter of 2002.[31] Households in the CEX report their quarterly consumption for four consecutive quarters. We exclude households that only stay in the sample for one quarter or with unusual data.[32] Our sample consists of 53,241 households, for a total of 182,716 quarterly observations. Table 2 shows summary statistics for the full CEX and for our estimation sample. The CEX provides sampling weights, which we adjust using age and rental status to account for the fact that attrition and incomplete income data are more common among young renters.[33] We use these adjusted sample weights to compute summary statistics that are representative of the U.S. population.

Table 1 reports two measures of the home energy burden: energy spending as a fraction of total pre-tax income and as a fraction of total consumption (see the Appendix for additional information). Since income may be subject to transitory shocks and/or mismeasured, total consumption provides a more accurate depiction of the household's permanent income, assuming that households do not suffer major liquidity constraints.

The first two rows of Table 1 depict key percentiles of the distribution of energy shares for our entire data set. These figures suggest that the median US household spends 3.4% of pre-tax income and 4.8% of total consumption on home energy. For most households, the vast majority of home energy costs are electricity bills. 76% of energy costs are for electricity in the median household. Gas and oil consumption are much more skewed, with over 25% of the households reporting no expenditures on gas and over 90% reporting no expenditures on oil. Oil use is concentrated in the Northeast, where it is used for home and occasionally water heating.

The next two rows of Table 1 report the same statistics excluding respondents who do not appear to be paying their electricity bills directly, for instance because they are living in subsidized housing where they are not responsible for utility costs. In our Euler equation estimates, we will exclude this group. Striking the approximately 12,000 observations with energy spending of zero in at least one quarter shifts the distribution of energy burdens upward. In this group, the median household spends about 5% of their budget on energy, while 25% of the households spend over 8%. Therefore, when energy prices rise by 15% (approximately the mean within-year difference between the minimum and maximum electricity price), these high expenditure households would need to cutback on either saving or consumption of all other goods by 1% if they do not reduce energy consumption. Put another way, since nondurable expenditures are

[31] We start our sample in 1990 because we lack earlier energy price data by state and month.
[32] We exclude consumer units with multiple households or student households. Following Lusardi (1996), we exclude households if they ever report a consumption change (in nondurables, food, or energy) of over 200% in absolute value; or if they are incomplete income reporters. We further exclude households if they ever have strictly nondurable consumption of less than $500 or food consumption of $0 in a quarter.
[33] This approach has been taken by John Sabelhaus and Ed Harris, who created the CEX extracts available through the National Bureau of Economic Research.

only 45% of total expenditures, if households cutback in this category in response to higher energy bills, they would need to cutback by nearly 3%.

The next six rows of Table 1 summarize the home energy burden for low-asset households, low-income households, and low-income elderly households, all of whom spend a greater share of their budget on energy. In households lacking substantial financial assets (defined as those households reporting no interest or dividend income), the median household spends 4.1% of its budget on energy.[34] The situation is starker for those with no assets at all or with low income. For example, the median household below the poverty line spends 7.2% of its budget on energy. Poor households with elderly members spend more on energy at every income level. In comparison, less than 1% of consumption for the median elderly poor household is for prescription drugs during these years.

There are several explanations for the disproportionate share of energy expenses in low-income budgets. First, keeping a dwelling lighted and temperate (warm in the winter and cool in the summer) requires a baseline amount of energy, so the energy share of expenditures does not rise as quickly with income as do many other expenditures. Second, while low-income households tend to live in smaller spaces, their dwellings are less well insulated and use less efficient heating sources. For example, the CEX asks respondents how they heat their house, using electricity, natural gas, oil or something else. Low-income consumers are less likely to use gas and more likely to use an inefficient heating source such as electricity, bulk fuels or wood (see the Appendix Table and Table 2). While low-income households use much less energy for cooling purposes, but those that do spend a greater fraction of their income on cooling.[35]

To sum up, households spend enough on home energy that variation in fuel prices and weather can require a significant adjustment elsewhere in the budget. This is especially true for poor and elderly households.

5. Fuel Price and Weather Variations

The key variables that we use to predict energy expenditures are monthly fuel prices and heating and cooling degree days by state. Since our estimation strategy requires predictable and unpredictable variation in prices and weather over time and across states, this section presents some summary statistics on our price and weather data. Further details on the sources for these variables are provided in the data appendix.

Figures 1a-e depict the national average trends in our price and weather data. There is a strong seasonal pattern in all series. Weather exhibits more variability than prices in our sample, with more variability in heating degree days (i.e., cold weather) than in cooling degree days. The heat waves of 1995 and 1998 and the harsh winter of 1993 stand out in figures 2c and 2e. Of the fuels, there is generally more variation over time in electricity and gas than in heating oil prices. There is a strong seasonal pattern in all except the heating oil series. Average electricity prices over the

[34] We draw attention to those households at this point because we find key differences for them in the estimation results later on.
[35] See HHS (1999) and Economic Opportunity Research Institute (1999) for more detailed explanations of the variation in home energy burdens across households.

annual seasonal cycle fell steadily through the 1990s and then climbed slightly in 2001. Average natural gas prices remained relatively steady through the 1990s and then climbed slightly in 2000 and 2001. Home heating oil prices show a similar increase in the later years of the sample, but show a much less pronounced seasonal cycle and more variability. For gas and electricity, changes in input prices and changes in the regulatory framework drive variations over time.

An individual state's experience, even with fuel prices, can differ substantially from the national average. For example, the average electricity price is over twice as high in several Northeastern states as in some Western and Appalachian states. Variation in electricity prices across states is driven by a number of factors, including the fuel used to generate electricity in the state (hydropower is inexpensive, so states that rely heavily on hydropower, including Washington, Idaho and Oregon, have the lowest average prices), regulatory policies faced by the utilities in the state as well as the general cost of doing business (e.g. average blue-collar wages, property taxes, etc.). The cross-state range in gas prices is similar to that of electricity, while the range in heating oil prices is somewhat smaller.

Table 3 reports results from ANOVA analysis of the weather and price variables. Nearly all of the variation in weather data is explained by month and state, leaving less than 3% that is unexplained. In contrast, about three-quarters of the variation in electricity and gas prices and less than one-third of the variation in fuel oil prices is explained by month and state.

We will treat state-month variation as anticipated. Moreover, trends are small enough that it makes little difference whether we allow for the formation of expectations over a short or long time period. For example, we have considered the average by state and month over the entire sample period, excluding the current observation, and moving averages of anywhere from two to six years. For almost all the weather and price variables, the correlation coefficient among these measures exceeds 0.93. For heating oil prices, the lowest correlation is 0.67, for the 2-year moving average and the average over the entire sample. Therefore, for now we will treat the weather and price variables as stationary, using data from the full sample period to compute their anticipated components. We intend to adjusting our measures of anticipated prices for a trend in future work. We obtain very similar results if we use the short (2-year) moving averages.

We compute unanticipated variation as the deviation of the weather and price variables from their anticipated values by month and state. In our sample, some states exhibit greater unpredictable variation than others in weather and prices. When we compute the average unanticipated variation within states over time, it is highest for gas and electricity prices and lower for weather and heating oil prices.

6. Estimation results

6.1 Predicting home energy expenditures

We present results from estimating equation (5) in levels in Table 4a and estimating equation (6) in logs in Table 4b. Each table reports results from two specifications, one which includes only weather and price variables and a second which also adds interaction terms between weather and prices. For each specification, we include variables measuring both anticipated and unanticipated changes, but we report the coefficient estimates in separate columns to facilitate comparisons across the estimates. The coefficients in the first and third columns of Tables 4a and 4b were estimated together in specification (1), and the coefficient estimates in the second and fourth columns were estimated together in specification (2).

Consider, first, specification (1), without the price-weather interaction terms. In both tables all of the coefficient estimates take the expected sign (positive), except for unexpected changes in electricity prices, which have a negative, small and insignificant effect in both tables. The weather variables are highly significant, and both the anticipated and unanticipated variables yield high overall F-statistics. Except for the fuel price variables, the anticipated variables have slightly more predictive power than the unanticipated variables. The magnitudes of the coefficients suggest that energy bills respond more to additional anticipated cooling degree days than to additional anticipated heating degree days, while the effects of the unanticipated weather variables are in between the effects of anticipated weather and close to one another.

When we add interaction terms, some of the significant coefficients are negative, suggesting that demand is more price responsive when the weather is less temperate, and some are positive, suggesting the opposite. In light of the fact that electricity bills comprise almost three-quarters of the typical home energy bill, it is puzzling that the electricity price coefficient estimates and the interactions involving electricity prices, particularly with cooling degree days, are insignificant. That result does not appear to be driven by correlations between electricity, natural gas and oil prices.

6.2 Induced changes in non-energy expenditures

Tables 5a and 5b report coefficient estimates from the Euler equations. In both tables, each reported coefficient derives from a separate specification. The specifications in Table 5a use 2SLS, with changes in price and weather instrumenting for changes in energy spending levels. The specifications in Table 5b use $\Delta\ln(EN\hat{E}RGY)$ to instrument for $\Delta(ENERGY)$ and then include controls for the unanticipated weather and price variables to isolate the effect of $\Delta(ENERGY^{ANT})$ in the anticipated specification and for the anticipated weather and price variables to isolate the effect of $\Delta(ENERGY^{UNANT})$ in the unanticipated specification. The first two rows in each table report results using just the weather and fuel price variables as instruments, corresponding to specification (1) in Tables 4a and 4b. The middle two rows add the weather-price interaction terms corresponding to specification (2), and the last two rows use price and the weather price interaction to predict changes in energy spending while including changes in weather as a control variable. For each pair of rows, results using anticipated variation are presented above the results using unanticipated variation. Results in the left-most column have ΔC_{Food} on the left hand side, results in the middle column $\Delta C_{Strictly\ nondurables}$ have on the left-hand side, and results in the right-most column $\Delta C_{nondurables}$ have on the left-hand side.

For all six specifications within all three expenditure categories, the results suggest an insignificant or even slightly positive change in consumption in response to anticipated changes in energy expenditures. Until we include weather in the second stage, the coefficient on $\Delta C_{nondurables}$ is positive and somewhat precisely estimated. The main categories that are included in nondurables and not in strictly nondurables are apparel, health and education. Consumption in these categories appears positively correlated with anticipated weather variation, as we hypothesized earlier.

In contrast, the results suggest large negative responses to changes in unanticipated energy expenditures, and the negative coefficients are statistically significant for five out of the six specifications when $\Delta C_{\text{Strictly nondurables}}$ is on the left-hand side. Besides food, the strictly nondurable category includes personal care, alcohol, tobacco, and household operations. Households appear to cut back on these non-food categories when energy bills spike.

We proceeded to estimate Euler equations separately for households that are more and less likely to be liquidity constrained. For this purpose, we used a variable indicating whether a household had received any interest or dividend income. As shown in Table 2, only 25.1% of the sample had received this type of investment income, so this is a group that is relatively well-off and financially savvy.

We separately estimated specifications for savers and non-savers analogous to those in the middle of Table 5b. Thus, we use $\Delta C_{\text{Strictly nondurables}}$ on the left-hand side; include weather, price, and weather-price interactions; and predict $\Delta\ln(ENERGY)$ in order to instrument for $\Delta(ENERGY)$.[36] The coefficient estimates of reactions to anticipated variation in energy are both small and insignificant, with -0.054 (0.110) for non-savers and 0.047 (0.191) for savers (compared to -0.051 (0.077) for the full sample in Table 5b).

In contrast, reactions to the unanticipated variation were -0.408 (0.149) for non-savers -0.067 (0.489) for savers (compared to -0.369 (0.182) for the full sample). Thus, the reaction to unanticipated disposable income changes is isolated to those without substantial financial assets. These non-savers are much more likely to ramp down non-durable consumption when surprised by higher energy bills, decreasing nondurable consumption by roughly 40 cents for each dollar by which they are surprised. We will continue to explore measures of heterogeneity across households in order to learn more about these reactions to unanticipated income shocks.

7. Conclusion

In this paper, we analyze how consumption of households responds to exogenous changes in home energy costs. We distinguish changes in energy spending that are anticipated, for instance because it is winter in the Northeast, from those that are unanticipated, for instance because it is an unusually cold winter. Anticipated changes in home energy spending should not affect consumption in a standard life-cycle model. Unanticipated transitory changes of the magnitude we study should affect consumption to a minor degree, as long as households are not liquidity-constrained; and they should have even smaller effects if households have accumulated precautionary savings to buffer such shocks. We focus in particular on households lacking substantial financial assets, as they may be less able to handle the shifts in disposable income.

We estimate several specifications and use different instrument sets. We find no evidence of excess sensitivity to anticipated variation in disposable income, even among households without substantial financial assets. By itself, this could be viewed as confirming results from some of the recent literature which suggest that households smooth consumption when faced with

[36] The F-statistics from the first-stage estimates for the savers were 12.26 ($p<.001$) for unanticipated variables and 22.36 ($p<.001$) for anticipated variables. The F-statistics for non-savers were 33.87 ($p<.001$) and 34.57.

regular, well-understood changes in disposable income. The magnitude of the anticipated changes that we examine is smaller than those in Hsieh (2003) and Browning and Collado (2001), suggesting that households will change their consumption paths even for small anticipated changes if they are simple to predict. This finding stands in some contrast to the explanation offered by Browning and Crossley (2000) to reconcile conflicting evidence about excess sensitivity in the recent literature; they argued that households appear more likely to smooth larger anticipated income changes because the welfare loss from not doing so is higher.

We find a different reaction to unanticipated income shocks among households without substantial financial assets. Our measure of possible liquidity constraints distinguishes those who receive interest or dividend income and are thus relatively well-off and financially savvy. Such households comprise only about 25% of our sample. Among the rest, who are more likely to be liquidity constrained, we find that consumption swings by about 40 cents for each dollar's worth of surprise in home energy costs – a quite large effect.

As such, the results provide mixed evidence about the nature of deviations from the LC/PIH. On the one hand, even households without substantial financial assets have enough liquidity to smooth out anticipated changes in disposable income, possibly using strategies besides dissaving to protect consumption – for example, by adding to credit card debt or working a little extra. On the other hand, households do not do a good job of buffering the unanticipated, yet relatively small, variation arising from weather and fuel price extremes.

A preliminary conclusion is that the effect of liquidity constraints depends on the nature of the change in disposable income, so perhaps some planning is necessary to avoid liquidity constraints. This supports the notion that the saliency of the anticipated income changes matters. However, the response to unanticipated income shocks suggests that liquidity constraints can be severe in other cases, and, moreover, that households take few precautionary steps that allow them to buffer sources of uncertainty in future consumption.

We will extend this research by investigating the mechanisms by which households in the CEX smooth out anticipated spending changes, though we may be limited by the poor quality of the asset data. We can also distinguish the effects of positive versus negative changes in resources and the responses of young versus old households (who perhaps face more versus less liquidity constraints). Thus, we hope to learn more about the nature of liquidity constraints and saliency.

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Data Appendix

Energy Prices

Data on state-level monthly energy prices for our sample period (1990-2002) come from several sources. For electricity prices, we use the data provided by the Energy Information Administration (EIA) in the Electric Power Monthly. This publication lists the average revenue per kilowatt-hour for residential households by state for each month. Summary statistics on the electricity price variable are shown in the first row of the table below. The average difference between the minimum and the maximum within a state in a given year is 16% of the mean price.

The average difference between the minimum and the maximum and the maximum across states in a given month is 106% of the mean price.

Information on natural gas prices comes from the EIA publication Natural Gas Monthly. The prices reflect the average revenue per thousand cubic feet. Both within state-year and within month price variation in natural gas is much more pronounced than for electricity, as shown in the second row of the table below.

Since most utilities use nonlinear pricing, some of the variation in the average revenue will be driven by changes in consumption patterns. For instance, if the utility uses a simple two-part tariff, the average revenue per kilowatt-hour sold will be lower when demand is higher, e.g. in the summer if there is more demand for electricity for air-conditioning than in the winter for heating. We have also accessed data from the Bureau of Labor Statistics (BLS) on the price for a fixed amount of natural gas, electricity or fuel oil. The disadvantage of the BLS series is that they are only available for a select group of cities, so we do not have information for every state.

Information on home heating oil prices comes from Petroleum Marketing Monthly, an EIA publication. The publication lists residential home heating oil (no.2 distillate) prices by month for approximately 20 states and for 5 Petroleum Area Districts (PADs). The PADs are comprehensive, so for states for which prices are not broken out separately, we use the appropriate PAD price. For some PADs, prices during certain months were not reported, apparently to avoid disclosure of individual company data. For these, we used predicted price levels from a regression of prices in the regions with missing data on prices from other regions.

Heating and Cooling Degree Days

The heating and cooling degree day data are from the National Climatic Data Center, NOAA, historical climatological series (HCS). Degree days are available by state (for the 48 continental states and DC treated as part of Maryland) and by month for our sample period (1990-2001). Heating degree days are calculated as a base temperature less the mean temperature for a day (i.e. if the mean temperature is 50°F and the base temperature is 65°F, that day is assigned 15 heating degree days). Cooling degree days are analogously calculated as the mean temperature for a day less a base temperature. Monthly degree days are the sum of daily degree days across the month. The state average totals are derived from state division values weighted by the percentage of the state population in each division (based on the most recent Census) to capture conditions for the typical resident.

Summary Statistics for State-level Monthly Data for 1990-2001

	Mean	Std. Dev.	Within State-Year (Max-Min)/Mean	Within Month (Max-Min)/Mean	N
P_{Elec} (cents/kwh)	8.89	2.38	0.17	1.07	7203
P_{Gas} ($/mcf)	8.16	2.26	0.45	1.00	7203
P_{Oil} ($/gallon)	101.31	17.71	0.22	0.38	7203
Heating Degree Days/100	4.37	4.18	2.50	2.82	7203
Cooling Degree Days/100	0.89	1.41	4.08	13.55	7203

Note: These data are monthly by state for the period 1990 to 2002. Our analysis excludes Alaska and Hawaii because information on heating and cooling degree days is unavailable. All numbers are in $2000.

Expenditure Data

The individual-level data we use in our primary analysis is from the Consumer Expenditure (CEX) Interview Surveys 1990:1 through 2002:1. The CEX interviews approximately 5,000 households every quarter on a rotating basis. Households are interviewed for four consecutive quarters and then dropped from the sample. Each quarter, households provide detailed reports of expenditure by category for the prior three months. The Interview Surveys are designed to collect data on expenditures on relatively large purchases and on regular expenses that the respondent is likely to be able to recall retrospectively. Combined with global estimates for food, BLS estimates that approximately 90 to 95 percent of all expenditures are captured. Information on income for the prior year is gathered in the last interview, which coincides with the timing of annual consumption over the course of the quarterly interviews.

The most specific information available from the Interview Surveys is compiled in the Detailed Expenditure files. These files provide information a variety of variables that help us to capture heterogeneity in energy needs and responsiveness to changes in weather and prices, such as heating source, whether the household pays for utilities through a budgeted plan, and whether utilities are included in rent.

The CEX sample is a national probability sample selected to represent the noninstitutionalized resident population. We exclude student households, households where there are multiple consumer units, households for which there is only one observation, households in Alaska or Hawaii, any household that ever has quarterly food consumption of $0 or nondurable consumption less than $500, and households who are incomplete income reporters. We also drop observations if the previous interview is missing and observations reflecting quarter-to-quarter changes in log consumption greater than 2 or smaller than -2 in any of the four categories we consider. In all, we use almost 70% of the full sample.

We merged the state-level data on energy prices and weather to the consumption data using the state identifiers provided by the CEX. Unfortunately, we only have the state of residence for 80% of the households. For confidentiality reasons, the CEX excludes the state of residence if the state plus other demographic variables would identify the household as a member of a group of less than 100,000 people (e.g. a family of five living in a large city in Oregon with income greater than $100,000 per year). For households where the state was suppressed, we use all available information on the region of residence and/or urbanicity to match the household with average price and weather information to the most disaggregated group of states possible. For instance, if we know that the household is from the rural West, we use information on rural population by state to develop weighted average price and weather variables across the Western states. For households without region information, which are all rural households, we use the rural weighted national average. Finally, because the price variables are monthly and the consumption data are quarterly, we use average prices and total degree days over the three month period.

<u>Expenditure Categories</u>

C_{Energy}	Total expenditures on home energy, including electricity, fuel oil, natural gas, bottled gas, wood, and other fuels.
C_{Food}	Food at home, food received as pay, and food on premise.
C_{Nondur}	Nondurable expenditures, NIPA definition.
$C_{StrictlyNondur}$	Nondurable expenditures, definition from Lusardi (1996). Excludes expenditures

on apparel, health, education, and reading from the NIPA definition.

Income

$Y_{After\ TaxTotal}$ Before tax income less total taxes paid. Total taxes paid include federal, state, and local income taxes and personal property taxes.

$Y_{BeforeTaxTotal}$ Total earned and unearned income. Earned income includes wages and salaries and net profits from businesses and partnerships. Unearned income includes interest income, dividends, royalties, rental properties, public and private retirement payments, regular alimony and child support payments, transfers (e.g. Supplemental Security Income, welfare), and payments from social insurance programs (e.g. unemployment insurance, workers' compensation).

Figure 1a: (Real) Electricity Prices Jan. 1990-Mar. 2002

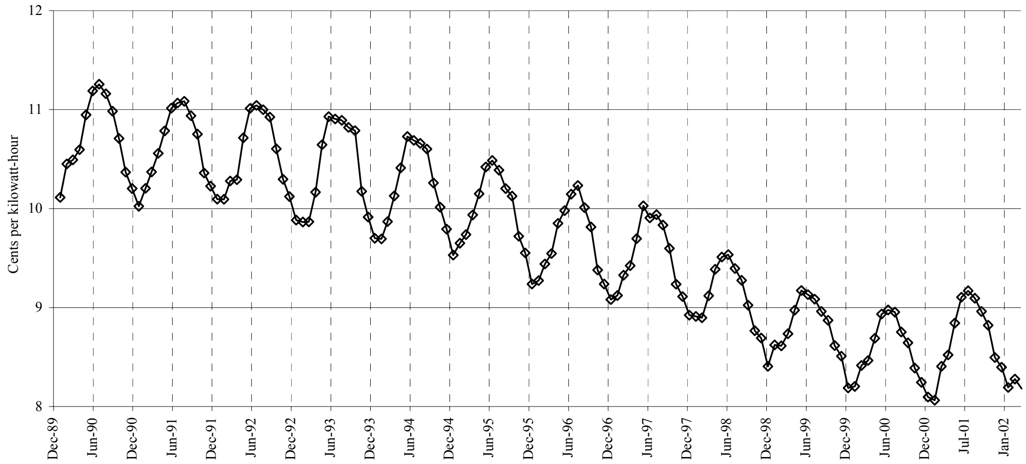

Figure 1b: (Real) Natural Gas Prices Jan. 1990-Mar. 2002

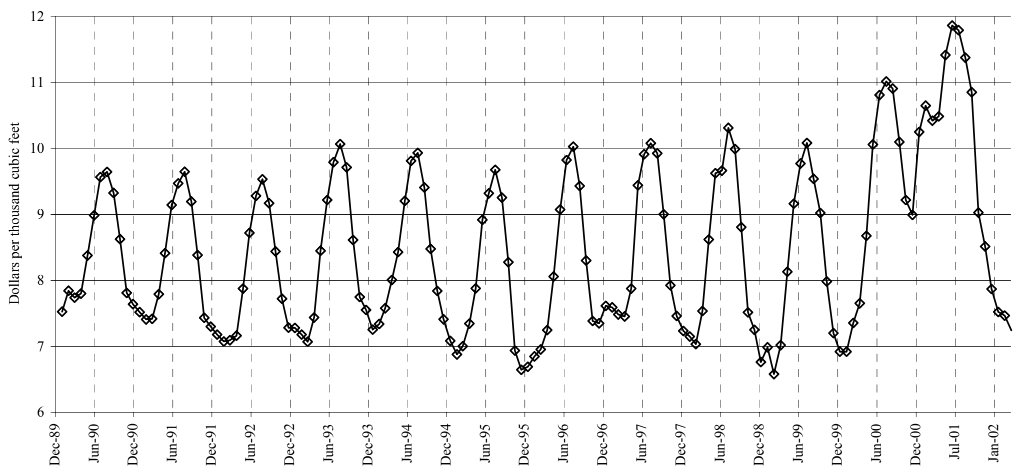

Figure 1c: (Real) Home Heating Oil Prices Jan. 1990-Mar. 2002

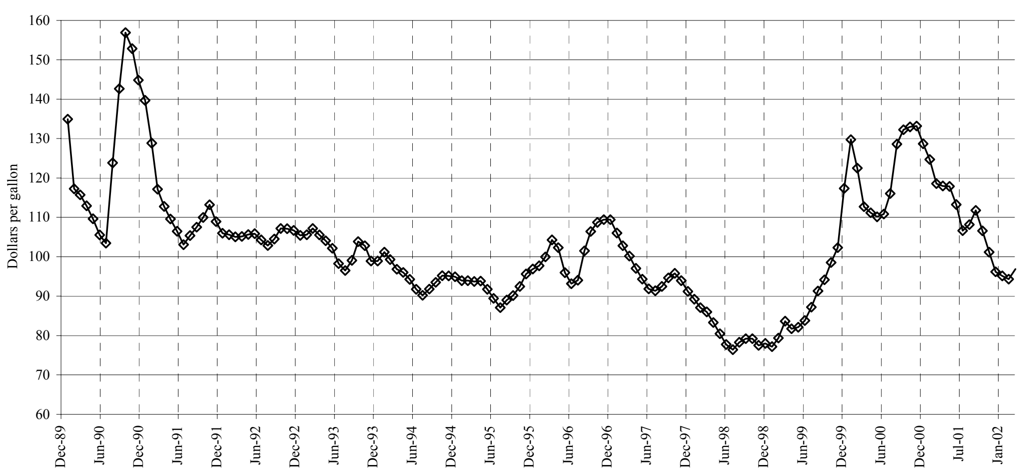

Figure 1d: Heating Degree Days Jan. 1990-Mar. 2002

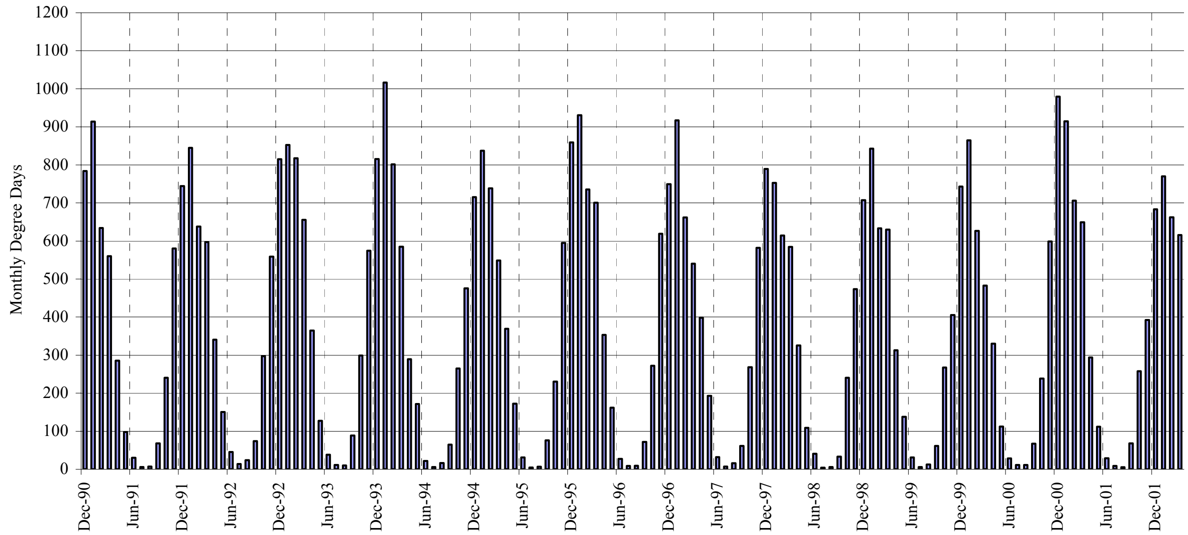

Figure 1e: Cooling Degree Days Jan. 1990-Mar. 2002

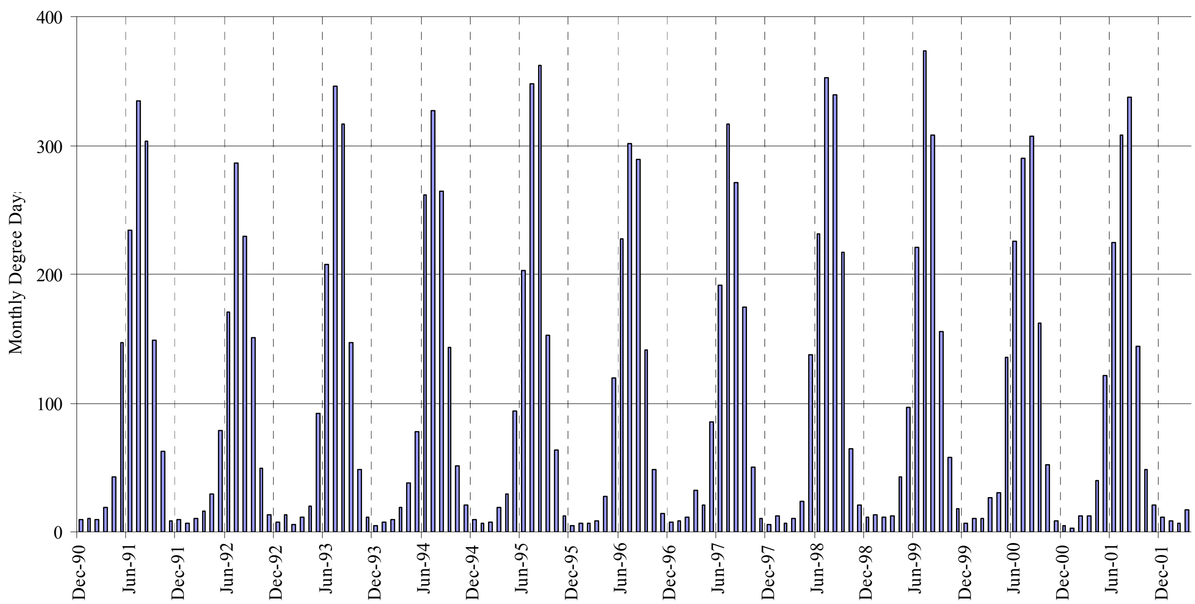

Table 1: Energy as a Fraction of Income and Total Expenditures 1990-2002

	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
All Households					
(N=182,716 household-quarter observations)					
Energy/Income	.009	.019	.034	.066	.128
Energy/Total Expenditures	.013	.027	.048	.078	.118
All Households Who Pay Energy Bills Directly					
(N=170,498)					
Energy/Income	.013	.021	.037	.069	.132
Energy/Total Expenditures	.018	.031	.051	.081	.120
Among Households who Pay Energy Bills Directly:					
Income < 100% Poverty					
(N=19,395)					
Energy/Income	.048	.081	.139	.252	.584
Energy/Total Expenditures	.026	.043	.072	.115	.167
Income 100-200% Poverty					
(N=35,030)					
Energy/Income	.027	.042	.066	.101	.146
Energy/Total Expenditures	.023	.039	.065	.100	.145
Household Head/Spouse 65+ & Income < 200% Poverty					
(N=19,113)					
Energy/Income	.039	.060	.095	.150	.238
Energy/Total Expenditures	.029	.048	.079	.121	.173
No Assets					
(N=26,417)					
Energy/Income	.019	.033	.062	.119	.224
Energy/Total Expenditures	.023	.039	.065	.104	.153
No Interest or Dividend Income					
(N=123,536)					
Energy/Income	.014	.023	.041	.078	.149
Energy/Total Expenditures	.019	.032	.054	.085	.127

Source: Authors' calculations from the CEX.
Note: The poverty level is defined for pre-tax income using the Federal Poverty Guidelines (see http://aspe.os.dhhs.gov/poverty/figures-fed-reg.htm) and varies as a function of the number residing in the household.

Table 2: Summary Statistics for Households in the Consumer Expenditure Survey

	CEX	Selected sample		By Income Relative to Poverty Line (if pays utilities directly)			
	All	Estimation sample	Doesn't pay utils directly	< poverty line	100-200%	200-300%	> 300%
Income							
$Y_{\text{After TaxTotal}}$ (annual)	36089	43831	28855	8471	19173	32268	71157
	(37149)	(38958)	(32113)	(6616)	(7916)	(11132)	(41517)
Below the poverty line	.280	.139	.282	1	0	0	0
100-200% of poverty line	.191	.221	.280	0	1	0	0
200-300% of poverty line	.151	.175	.150	0	0	1	0
>300% of poverty line	.378	.465	.289	0	0	0	1
Wealth							
No assets	.196	.187	.375	.528	.254	.141	.051
No interest, div income	.739	.749	.851	.937	.851	.750	.635
Consumption (quarterly)							
C_{Total}	7787	7892	5669	4839	5647	6996	10425
	(6779)	(6630)	(5083)	(4220)	(4439)	(4816)	(7766)
$C_{\text{Nondurable}}$ (NIPA)	3635	3553	2704	2400	2764	3271	4464
	(2894)	(2628)	(2100)	(1788)	(1742)	(1829)	(3124)
$C_{\text{Strict nondurable}}$ (Lusardi)	2609	2524	2009	1810	1961	2320	3130
	(2041)	(1780)	(1518)	(1247)	(1255)	(1305)	(2074)
$C_{\text{Strict nondurable w/o transport}}$	2153	2114	1714	1566	1668	1947	2590
	(1745)	(1523)	(1334)	(1067)	(1086)	(1135)	(1786)
C_{Food}	1374	1329	1092	1036	1069	1244	1595
	(1000)	(887)	(774)	(690)	(684)	(727)	(1001)
Energy Spending							
C_{Energy} (quarterly)	388	356	89	329	343	368	409
	(294)	(247)	(207)	(229)	(213)	(223)	(249)
Heats with electricity	.242	.275	.317	.281	.282	.277	.262
Heats with gas	.544	.532	.448	.518	.517	.516	.561
Heats with oil	.121	.099	.110	.081	.093	.100	.105
Sample Size							
Observations	417,073	182,716	12,218	19,395	35,030	29,982	86,091
Households	121,106	53,241	3,857	5,772	10,203	8,701	24,708

Source: Authors' calculations from the CEX.
Note: Cells show sample means for household-quarter observations (standard deviations in parentheses). All dollar values in $2000.

Table 3: Sources of Explained Variation in Weather and Prices

	% of variation that is explained by: month	state	month*state	% of variation that is unexplained
ΔHeating Degree Days/100	90	<1	10	<1
ΔCooling Degree Days/100	76	<1	21	3
$\Delta\ln(P_{Elec})$	33	<1	48	18
$\Delta\ln(P_{Gas}$	63	<1	16	21
$\Delta\ln(P_{Oil})$	20	<1	7	73

Note: Results from ANOVA estimates on the variables in the first column. The sample consists of state-month observations from January 1990 through March 2002, excluding Alaska and Hawaii. The independent variables are calendar month, state of residence, and month interacted with state. The values of the variables in the first column are the same as the values used in the log CEX regressions that appear later: for weather variables, we compute the quarter-to-quarter change in the average value; for price variables, we compute the quarter-to-quarter change in the natural log of the average price.

Table 4a: Predicting Changes in Energy Expenditures in Levels

Dependent Variable = ΔC_{Energy}	Coefficients on Anticipated Variables		Coefficients on Unanticipated Variables	
	Specification:			
Independent Variables	(1)	(2)	(1)	(2)
ΔHeating Degree Days/100	3.758***	5.072**	5.018***	5.357*
	(0.680)	(2.400)	(1.154)	(2.896)
ΔCooling Degree Days/100	11.189***	5.807	6.157***	-0.148
	(1.291)	(4.408)	(0.472)	(1.299)
ΔP_{Elec}	4.594	8.582	-0.853	-3.842
	(6.523)	(7.093)	(2.882)	(3.300)
ΔP_{Gas}	5.388*	-0.140	11.451***	9.131***
	(3.182)	(3.507)	(2.162)	(2.262)
ΔP_{Oil}	3.650***	3.768***	0.533***	0.400***
	(0.901)	(1.137)	(0.128)	(0.140)
$\Delta(\text{HDDays}/100 \times P_{Elec})$		0.021		0.237**
		(0.104)		(0.090)
$\Delta(\text{CDDays}/100 \times P_{Elec})$		0.048		0.405
		(0.377)		(0.253)
$\Delta(\text{HDDays}/100 \times P_{Gas})$		0.584***		0.444***
		(0.150)		(0.092)
$\Delta(\text{CDDays}/100 \times P_{Gas})$		0.677***		-0.385**
		(0.183)		(0.152)
$\Delta(\text{HDDays}/100 \times P_{Oil})$		-0.058**		0.001
		(0.022)		(0.005)
F-test for joint significance of:				
All weather/price variables	F=60.64	F=101.32	F=53.89	F=34.72
	[p<.001]	[p<.001]	[p<.001]	[p<.001]
Weather variables	F=120.33	F= 2.26	F=91.10	F=2.27
	[p<.001]	[p=.116]	[p<.001]	[p=.115]
Price variables	F=6.22	F=3.73	F=16.58	F=11.41
	[p=.001]	[p=.017]	[p<.001]	[p<.001]
Interactions		F=7.47		F=19.73
		[p<.001]		[p<.001]
Interactions + price variables		F=8.98		F=23.21
		[p<.001]		[p<.001]
Number of Observations	121,114	121,114	121,114	121,114

Note: Specifications (1) and (2) included both anticipated and unanticipated price and weather variables. We report them in separate columns to improve legibility. Both specifications include year and month fixed effects to capture secular and seasonal trends as well as demographic characteristics, including a fourth order polynomial in reference person age, a linear term in family size, dummy variables change in family size, change in children under 2, under 6 and under 18 and a new worker in the household. Robust standard errors in parentheses control for serial correlation at the state level.

Table 4b: Predicting Changes in Energy Expenditures in Logs

Dependent Variable = $\Delta\ln(C_{Energy})$	Coefficients on Anticipated Variables		Coefficients on Unanticipated Variables	
	Specification:			
Independent Variables	(1)	(2)	(1)	(2)
Δ(Heating Degree Days/100)	0.005***	0.056**	0.014***	0.038***
	(0.002)	(0.027)	(0.003)	(0.013)
Δ(Cooling Degree Days/100)	0.038***	0.014	0.013***	-0.002
	(0.004)	(0.024)	(0.001)	(0.008)
$\Delta\ln(P_{Elec})$	0.163	0.451***	-0.027	-0.019
	(0.154)	(0.146)	(0.060)	(0.067)
$\Delta \ln(P_{Gas})$	0.008	-0.114	0.252***	0.224***
	(0.063)	(0.075)	(0.058)	(0.060)
$\Delta \ln(P_{Oil})$	0.182	0.530*	0.051	0.048
	(0.254)	(0.275)	(0.034)	(0.029)
Δ(HDDays/100 x $\ln(P_{Elec})$)		-0.007***		0.002
		(0.002)		(0.002)
Δ(CDDays/100 x $\ln(P_{Elec})$)		-0.013*		-0.002
		(0.007)		(0.005)
Δ(HDDays/100 x $\ln(P_{Gas})$)		0.010***		0.003***
		(0.003)		(0.001)
Δ(CDDays/100 x $\ln(P_{Gas})$)		0.024***		-0.009***
		(0.007)		(0.003)
Δ(HDDays/100 x $\ln(P_{Oil})$)		-0.012**		0.001
		(0.006)		(0.001)
F-test for joint significance of:				
All weather/price variables	F=62.93	F=36.32	F=41.47	F=32.75
	[p<.001]	[p<.001]	[p<.001]	[p<.001]
Weather variables	F=90.91	F= 3.62	F=64.89	F=5.33
	[p<.001]	[p=.008]	[p<.001]	[p=.008]
Price variables	F=0.38	F=5.41	F=9.05	F=6.65
	[p=.765]	[p=003	[p=.017]	[p=.001]
Interactions		F=5.54		F=10.70
		[p<.001]		[p<001
Interactions + price variables		F=6.76		F=11.00
		[p<.001]		[p<001
Number of Observations	121,114	121,114	121,114	121,114

Note: See Table 4a.

Table 5a: Consumption Responses to Energy Expenditure Fluctuations-Level IVs

Energy Instrument Set	Estimation Method		Dependent Variable ΔC_{Food}	$\Delta C_{Strictly\ nondurables}$	$\Delta C_{Nondurables}$
Weather and price IVs for ΔC_{Energy}	2SLS	*Anticipated*	-0.029	-0.017	0.214
			(0.069)	(0.069)	(0.144)
		Unanticipated	-0.171	-0.410	-0.370
			(0.197)	(0.252)	(0.379)
Weather and price plus weather*price, IVs for ΔC_{Energy}	2SLS	*Anticipated*	-0.062	-0.058	0.138
			(0.065)	(0.070)	(0.150)
		Unanticipated	-0.144	-0.388**	-0.342
			(0.163)	(0.204)	(0.284)
Price plus weather*price, IVs for ΔC_{Energy} Controlling for weather.	2SLS	*Anticipated*	-0.169	-0.022	-0.309
			(0.227)	(0.314)	(0.611)
		Unanticipated	-0.282	-0.619**	-0.401
			(0.225)	(0.325)	(0.410)

Note: The dependent variables is as indicated in each column. The specifications include the baseline demographic and time variables. Standard errors are corrected for within state correlation.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5b: Consumption Responses to Energy Expenditure Fluctuations-Log IVs

Energy Instrument Set	Estimation Method		Dependent Variable ΔC_{Food}	$\Delta C_{Strictly\ nondurables}$	$\Delta C_{Nondurables}$
Weather and price in logs IVs for $\Delta \ln(C_{Energy})$	True IV	*Anticipated*	-0.036	-0.030	0.256
			(0.061)	(0.073)	(0.141)
		Unanticipated	-0.136	-0.383*	-0.385
			(0.167)	(0.196)	(0.325)
Weather and price plus weather*price in logs IVs for $\Delta \ln(C_{Energy})$	True IV	*Anticipated*	-0.040	-0.051	0.190
			(0.064)	(0.077)	(0.147)
		Unanticipated	-0.110	-0.369**	-0.323
			(0.156)	(0.182)	(0.282)
Price plus weather*price, IVs for $\Delta \ln(C_{Energy})$ Controlling for weather.	True IV	*Anticipated*	0.164	0.179	-0.150
			(0.343)	(0.568)	(0.770)
		Unanticipated	-0.230	-0.627**	-0.373
			(0.231)	(0.304)	(0.423)

Note: See Table 5a.