The Effects of Weather on Retail Sales

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ABSTRACT

Monthly fluctuations in consumer spending are often attributed to the weather. This paper presents a model in which weather affects the productivity of time in nonmarket activities (such as shopping or recreation), and so, via time and budget constraints, may induce substitution in spending across goods and over time. Using monthly data on retail sales and weather data from the National Weather Service, I find that unusual weather has a modest but significant role in explaining monthly sales fluctuations. However, lagged effects often offset original effects, so that weather's influence tends to wash out at a quarterly frequency.

JEL: E21, E32, D12 Consumption, retail sales, seasonal fluctuations, weather

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1. Introduction

Weather is often identified as the cause of month-to-month fluctuations in consumer spending. This is not a matter of regular seasonal variations, but rather exaggerations and departures from the seasonal cycle. Press reports on retail sales fluctuations during 1997 serve to illustrate the point. The unusually mild January 1997 was said to have brought consumers out to the stores and auto dealers' lots; a cool rainy spring kept them away from malls and restaurants; the return of seasonal weather in June sent them out to buy bathing suits and mountain bikes; and the unusually mild autumn delayed sales of cool weather attire.[1] Such arguments not only appear in the business press, but also figure into well-regarded macroeconomic forecasts: for example, both DRI and Macroeconomic Advisors predicted sizable dropbacks in consumer spending in the second quarter of 1997, after the first-quarter binge.

Despite the frequency of arguments like this, the effects of weather on consumer spending have received little serious attention in economic research. Some micro studies have investigated effects of weather on sales for specific stores or in specific locations: for example, a notable early study found that sales of New York City department stores dropped off on rainy days (Linden 1959). While such results suggest that widespread deviations from normal weather could affect aggregate spending, to date there has been no systematic analysis of weather effects in the national data. Understanding the effects of weather is important for economic forecasters and monetary policy, because it helps distinguish changes in the underlying pace of economic activity from transitory shifts. Also, examining this issue may provide some interesting insights into intertemporal variations in consumption: for example, conceivably, the well-known lagged

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[1]See, for example, Hershey (1997a and 1997b).

effects of income on consumption may in part reflect a role of practical considerations like weather.

This paper examines the effects of weather on retail sales. After first reviewing basic seasonalities in retail sales, I present an analytical framework for thinking about how and why unusual weather may cause fluctuations in spending. This effect rests on the notion that weather affects the productivity of time in nonmarket activities (such as shopping or recreation), and so, via time and money constraints, can induce substitution in spending across goods and over time. I also discuss how sales levels may be affected by retailers' incentives to clear out inventories. To examine effects of unusual weather, I use monthly data on retail sales from the Census Bureau's representative survey of retailers, along with weather data from the National Weather Service. I find that, even after taking other determinants of consumer spending into account, unusual weather has a modest but significant role in explaining monthly fluctuations in retail sales. However, lagged effects often offset original effects, tending to wash out at a quarterly frequency.

2. Background

To illustrate the basic seasonal patterns in retail sales, Table 1 presents data from the U.S. Census Bureau's Monthly Retail Trade Survey -- the main source of high-frequency information on consumer spending and the data source used for this study. The survey is based on a random sample of about 12,000 retail establishments.[2] Each month, establishments report to the Census Bureau the total nominal value of their sales in the previous month. The sales data are released in both seasonally adjusted and unadjusted form.[3]

To describe basic seasonal patterns in retail sales, table 1 shows the distribution of retail sales over the year for different categories of retail establishments, using the seasonally *un*adjusted data. The figures are averages of each month's share of annual sales; thus, if sales

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[2]Until 1997, the survey had rotating panel design described in Wilcox (1992). Since then, the survey has been based on a fixed panel; see U.S. Census Bureau (1997).

[3]Seasonal adjustment is done using the X11-ARIMA method; adjustments are also made for trading days and holidays.

were evenly distributed over the year, the month's share would be 1/12 or 8.333%. The main seasonal pattern apparent in the data is the substantial pick-up in sales in November and December; almost 20 percent of total annual retail sales occur in these two months, with the share for general-merchandise outlets -- a category dominated by department stores -- exceeding 25 percent.[4] Of course, the holiday season plays an important role in this pick-up, along with sales of outerwear and other seasonal merchandise. For auto dealers, nominal sales peak in May and June, and drop way off between December and February. At building materials and supply stores, sales are strongest from May through August, while there is a pronounced lull in January and February. Sales at gas stations and restaurants are highest in July and August, reflecting summer travel. For food stores, monthly shares are relatively steady over the year, with a bit of a holiday pickup in December.

Some part of the basic seasonal pattern can be traced to the weather. Shifts in apparel sales reflect the need for different clothing when the seasons change. Shopping for a new car may be timed with mild, pleasant weather in mind. Summer travel plans complement pleasant outdoor weather and the desire to escape the heat. And home construction and repair activities depend on weather, dropping off considerably in the cold winter months. To the extent that seasonal weather changes are regular predictable patterns, they would not be expected to have effects on the seasonally adjusted data. But temperature, precipitation, and other weather-related factors vary considerably around seasonal norms, and so may affect the pace of seasonally-adjusted sales.

Figure 1 shows national data on temperatures -- the aspect of the weather that appears to matter most for broad-based weather-related fluctuations in spending.[5] The data come from the National Weather Service's "degree day" series, which are population-weighted measures of

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[4]See Appendix 1 for details on the types of stores included in each category.

[5]Some previous studies have examined other aspects of the weather, without finding much broad-based effect (e.g. Miron 1986). Some area- or store-specific studies have used very detailed weather measures; for example, Linden (1959) studied the effects on New York City department stores of rain, sunshine, temperature, and snow on the ground during business hours, finding few systematic effects. In studying effects of weather on construction activity in central England, Solomou and Wu (1997) use data on temperature, rainfall and frost, using nonlinear specifications to allow for the possibility that only extreme weather has appreciable effects.

average temperature. Degree days are computed as follows. For a given day at a given weather station, the average daily temperature is computed by adding the high and low temperatures at the station and dividing by two. If this number exceeds 65, the difference is considered to be the "cooling degrees" for the day; if the number is less than 65, the difference is considered to be the day's "heating degrees." For the month as a whole, "heating degree days" are the sum of the days' heating degrees while "cooling degree days" sum over the daily cooling degrees. For the U.S. overall, monthly heating degree days (HDD) and cooling degree days (CDD) are computed as population-weighted averages of degree days at the individual weather stations.

The figure shows that, not unexpectedly, HDDs are high in the winter and negligible in the summer, while the opposite is true for CDDs. There is a bit of a downtrend in HDD, reflecting both climatic warming and population shifts. Of course, for us what matters is not the regular fluctuations but temperatures that depart from seasonal norms. Because weather norms may be changing over time, it is useful to measure unusual temperatures as the deviation from a moving average of the monthly heating or cooling degree days for that month. Panels (b) and (d) of Figure 1 show such deviations, using a moving average for the past seven years. The deviations vary considerably from year to year, with some months much warmer or colder than in they have been in recent years. Thus, if consumer demand is influenced by departures from normal temperatures, such deviations may have appreciable effects.

3. Analytical considerations

Consumer decision. To think about how and why weather might affect consumer spending, it is useful to use Ghez and Becker's (1975) household-production approach to consumer decisions. In their framework, the consumer's utility is a function of n underlying commodities. Each commodity, C_{it}, is produced from household labor and purchased goods used in its production. The commodities may be unobserved, like "outdoor recreation" or "at-home entertainment"; it is the goods that are inputs into the production of commodities that are purchased, like in-line skates or beverages and chips.

Formally, the production function for commodity i in period t can be written as follows:

$$C_{it} \quad = \quad C_{it} \; (q_{it} \, , h_{it} \, , \theta_{it} \,) \qquad (1)$$

where $q_{it} = \{q_{1it} \dots q_{mit}\}$ is the vector of goods used to produce C_{it}, h_{it} is the household labor used, and θ_{it} represents factors that shift the productivity of goods or labor in the production of C_{it}. Then household utility in period t is a function of the n commodities consumed during that period:

$$U_t \quad = \quad U \, [\, C_1(q_{1t}, h_{1t}, \theta_{1t}), C_2(q_{2t}, h_{2t}, \theta_{2t}), \dots C_n(q_{nt}, h_{nt}, \theta_{nt})] \qquad (2)$$

Assuming no bequests, the household's lifetime budget constraint specifies that the present discounted value of all spending on goods must equal initial assets, A_0, plus the present discounted value of labor earnings, so that

$$\sum_t \frac{1}{(1+r)^t} \, [\, \sum_i \sum_j p_{jt} \, q_{jit} \,] \; = A_0 \; + \; \sum_t \frac{1}{(1+r)^t} \, w_t \, H_t \qquad (3)$$

where H_t is hours of paid work and w_t is the wage rate. Total time L_t is divided between paid work and household production:

$$L_t = H_t + \sum_i h_{it} \qquad (4)$$

so that the budget constraint can be re-written as:

$$\sum_t \frac{1}{(1+r)^t} \; \sum_i \, [\, w_t \, h_{it} \; + \sum_j p_{jt} \, q_{jit} \,] \; = A_0 \; + \; \sum_t \frac{1}{(1+r)^t} \, w_t \, L_t \qquad (5)$$

The household buys goods and allocates time across activities so as to maximize the present discounted value of utility:

$$U \quad = \quad \sum_t \delta^t \; U_t \qquad (6)$$

subject to the combined time and budget constraint (5). While the precise solution to the optimization depends on the functional form assumptions underlying (2), with a sufficiently flexible specification, it would be expected to yield a series of demands for goods of the following form:

$$q_{it}^* = q_{it}^*(w_t \ldots w_T ; P_t \ldots P_T ; \theta_t \ldots \theta_T ; \delta ; r) \tag{7}$$

where $\{ w_t \ldots w_T \}$ is the vector of current and expected wage rates, $\{ P_t \ldots P_T \}$ is the matrix of current and future prices, and $\{ \theta_t \ldots \theta_T \}$ is the matrix of factors that affect the productivity of resources in household production.

The point of this development is to show that, through intertemporal optimization and because of time and money constraints, an item like weather that affects nonmarket productivity may induce substitutions in spending across goods over time. At a general level, we can suggest several ways that unusual weather could affect demand for goods, holding prices and other factors constant.[6] First, weather can make shopping a more or less difficult experience. Cold temperatures and precipitation may hinder travel, keeping people away from stores and restaurants. Conversely, hot summer weather may drive them there in search of indoor diversions. Such "convenience effects" might be expected to have a disproportionate effect on discretionary or easily-postponed purchases, like furniture and apparel. Second, weather complements a number of outdoor recreational activities, like golf or going to the beach, which may divert people from shopping and into other pursuits. Third, certain goods complement activities related to the weather. For example, winter storms spur sales of snow shovels and sleds; early spring weather boosts sales of bicycles and inline skates; and sales of rainwear and umbrellas spike on rainy days (Linden 1959, Gagne 1997).

In addition to effects on current spending, unusual weather may also affect spending in future periods. First, convenience effects that cause a dip in retail sales may later be "made up,"

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[6]Unusual weather may also affect income, although such effects are not treated here.

while those spurring extra sales may later be "paid back." References to such lagged effects are extremely common in the business press.[7] Second, unusual weather may cause damage or wear-and-tear for items that will then need to be replaced.[8] To the extent that replacement does not take place immediately, sales may be above normal for some period following the unusual weather. A third effect pertains to early onsets of seasons, e.g. cool weather in early autumn or summer weather that starts in May. Such early turning points are said to boost demand early on in the season, in part because people think they will "get more use out of" seasonal merchandise.[9] This may shift the distribution of sales toward the early part of the season, and away from subsequent months.

Demand and supply. In addition to affecting consumer demand, unusual weather may also have effects on the supply side. For most retailers, all but the most extreme weather may have little effect on the current supply of goods. However, if poor weather weakens sales, retailers may increase supply in subsequent periods to clear out unwanted inventories.[10] One might expect such carryover effects particularly for fashion goods and seasonal items (Lazear 1986; Smith and Achabal 1998).

It is useful to develop a simple framework that captures this idea. Suppose that q_t^d is the log of the quantity demanded of a good, q_t^s is the log of the quantity supplied, and p_t is the log price. Let ω_t be the measure of the deviation from normal seasonal weather, assumed to affect current demand but not current supply. Then we can write:

$$q_t^d = \alpha_1 + \alpha_2 p_t + \alpha_3 \omega_t \qquad (8)$$

$$q_t^s = \beta_1 + \beta_2 p_t \qquad (9)$$

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[7]Linden (1959, p. 27) examined lagged effects on sales in the days after unusual weather, but found no evidence of them.

[8]For example, home repair items, air conditioners, and car batteries; see Gagne (1997).

[9]As Linden (1959, p. 28) writes, "A chill September means early shopping for fall wardrobes, a better season generally, and a hearteningly high proportion of weather-sensitive merchandise going at full mark-on. But a sultry autumn makes for sluggish performance on all counts."

[10]For information here, see Lazear (1986), Smith and Achabal (1998).

where we assume that $\alpha_2<0$ and $\beta_2>0$. Equilibrium price and quantity are given by:

$$p_t^* = \frac{\alpha_1 - \beta_1}{\beta_2 - \alpha_2} + \frac{\alpha_3}{\beta_2 - \alpha_2}\,\omega_t \tag{10}$$

$$q_t^* = \frac{\alpha_1\beta_2 - \beta_1\alpha_2}{\beta_2 - \alpha_2} + \frac{\beta_2\alpha_3}{\beta_2 - \alpha_2}\,\omega_t \tag{11}$$

Clearly, weather that reduces demand in period t ($\alpha_3<0$) will reduce the equilbrium price and quantity sold, and so will lower the total nominal value of sales.

In the period t+1, the quantity demanded is a function of price, the t+1 weather deviation, and any carry-over from the weather deviation in the previous period; we express the latter as a function of the difference between q_t^* and the quantity that would have been sold had the weather been normal, q_t^n. Quantity supplied is a function of the price and a similar carry-over term.

$$q_{t+1}^d = \alpha_1 + \alpha_2 p_{t+1} + \alpha_3 \omega_{t+1} + \alpha_4 (q_t^* - q_t^n) \tag{12}$$

$$q_{t+1}^s = \beta_1 + \beta_2 p_{t+1} + \beta_4 (q_t^* - q_t^n) \tag{13}$$

Then the equilibrium price and quantity would be:

$$p_{t+1}^* = \frac{\alpha_1 - \beta_1}{\beta_2 - \alpha_2} + \frac{\alpha_3}{\beta_2 - \alpha_2}\,\omega_{t+1} + \frac{(\alpha_4 - \beta_4)}{\beta_2 - \alpha_2}\,\frac{[\beta_2\alpha_3]}{\beta_2 - \alpha_2}\,\omega_t \tag{14}$$

$$q_{t+1}^* = \frac{\alpha_1\beta - \beta_1\alpha_2{}_2}{\beta_2 - \alpha_2} + \frac{\beta_2\alpha_3}{\beta_2 - \alpha_2}\,\omega_{t+1} + \frac{(\beta_2\alpha_4 - \alpha_2\beta_4)}{\beta_2 - \alpha_2}\,\frac{[\beta_2\alpha_3]}{\beta_2 - \alpha_2}\,\omega_t \tag{15}$$

These equations suggest several intuitions about how unusual weather in period t, ω_t, would affect the market in period t+1. First, for unusual weather that reduces demand in period t but raises it in t+1 ($\alpha_3<0$ and $\alpha_4>0$), q_{t+1}^* will be higher than it would have been in the absence of the unusual weather, as long as $\beta_4 \geq 0$. However, the effect on price is ambiguous, depending on how the shifts in demand and supply balance out; consequently, the change in the value of total sales will also be ambiguous. Second, even if unusual weather in period t does not affect demand in t+1 (α_4=0), q_{t+1}* may still rise if there is a carryover effect on supply ($\beta_4 > 0$). In this case, p_{t+1}* will be lower and q_{t+1}* will be higher than they would have been without the unusual weather, but again the effect on total sales is ambiguous. Finally, not unexpectedly, unusual weather that did not affect demand in period t (α_3=0) should have no effect on p_{t+1}* or q_{t+1}*.

4. Empirical Analysis

As mentioned, the Monthly Survey of Retail Trade provides monthly data on total nominal sales for different types of retail establishments. This provides a basis for estimating effects of unusual weather on total spending at various types of stores. However, there is no information on prices or physical quantities of goods sold, making it difficult to distinguish between effects of shifts in consumer demand and those of shifts in supply. Nonetheless, it is informative to see whether unusual weather has discernible effects on nominal retail sales, and if so, whether they are consistent with the types of predictions obtained from a simple model.

Monthly patterns. To analyze patterns in the monthly data, I estimate regressions of the following form:

$$\Delta \ln S_{it} = \alpha_i + Z_t{}'\delta + \sum_{s=0}^{3} \beta_{is}\, \omega_{t-s} + \varepsilon_{it} \tag{16}$$

where S_{it} is nominal retail sales in category i at time t, ω_t is the measure of unusual weather -- the deviation in heating or cooling degree days described above[11] -- and Z_t is a vector of other factors that may affect spending. Following other analysts, I include as "other factors" the lagged values of the following: the log change in real labor income, the percent change in real stock

[11]I also estimated the models using alternative measures of unusual weather, including deviations computed from five- and ten-year moving averages, and degree-day series seasonally adjusted by ARIMA X11. There are few qualitative differences in results.

prices, the change in the level of real interest rates, and the dependent variable.[12] The estimation period is 1967:1 through 1998:12. All hypothesis tests were conducted using a heteroskedasticity- and serial-correlation-robust covariance matrix, allowing serial correlation at lags up to 3.

Some basic results are shown in Table 2. The measures of unusual weather have clear value in explaining shifts in the pace of retail sales. Adding deviations in heating degree days increases the adjusted R-squared of the regression by 9.4 points, and these variables are jointly significant. Deviations in cooling degree days are also jointly significant, but have a smaller incremental R-squared of 3.9 points. Looking down the categories of retail establishments, the heating-degree measures have a relatively large incremental R-squared for building material and supply stores, consistent with well-known effects of weather on construction. Both heating and cooling degree day measures have large incremental R-squareds for general merchandise outlets and the GAF category, in line with the perception that department store sales are especially weather-sensitive. In contrast, the weather variables are not significant for food stores or gas stations.

The monthly pattern for heating degree days is shown in table 3. For total retail sales, unusually cold temperatures in a given month significantly depress sales growth in that month, but they lead to higher sales growth in the following two. The current and lagged effects do not completely offset each other, as indicated by the fact that the sum of the coefficients is positive and statistically significant. This dip-and-rebound pattern shows up for durable-goods stores as a whole and for different types of durable-goods stores, although for specific types of stores the sum of the coefficients is not uniformly statistically significant. The pattern is more mixed for nondurable-goods stores: sales bust and then boom for general-merchandise and apparel stores, as well as for restaurants, although there is no net positive effect over the four month period.

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[12]The model includes three lags of these variables. Following Carroll, Fuhrer, and Wilcox (1994), I define labor income as wages and salaries plus transfers minus contributions for social insurance. The measure of stock prices is the S&P 500, while the interest rate is that on a 3-month T-bill. The deflator used is the consumer price index for all urban consumers. Augmented Dickey-Fuller tests indicate that all the series used, including the weather measures, are stationary over the periods under consideration.

Taken together, these results suggest some tendency to postpone purchases of durable goods and other discretionary items when the weather is unusually cold, with the lost sales made up thereafter. The net effect on durables but not nondurables suggests some difference between the two, perhaps due to weaker pressures to mark down prices of durable goods and/or more of an element of replacement-demand for durables.

The results on cooling degree days are somewhat different (see table 4). For retail sales as a whole, unusually warm weather in a given month boosts sales in that month, but pulls down sales in the month after. The dropback offsets the pickup, with no significant net effect over the four month period. This pattern comes mostly from general-merchandise outlets, possibly consistent with perceptions that people flock to malls to get out of the heat, and/or buy seasonal merchandise early if warm weather comes early. However, this is not a general effect within the retail sector.

Effects on a quarterly basis.

We use a slightly different framework for analyzing the quarterly data, allowing for the possibility that weather effects may differ depending on the quarter in which they occur. Specifically, we measure unusual weather as heating-degree deviations in the first and fourth quarters, but cooling-degree deviations for the second and third quarters, and then estimate effects for that quarter and the quarter after.[13] Formally, the equation estimated is:

[13]In an average year in the 1967-98, 92 percent of heating degree days fell in Q1 and Q4, while 86 percent of cooling degree days fell during Q2 and Q3. I experimented with alternative specifications, finding the results to be fairly robust to changes in specification. I also estimated the models allowing unusual weather in a given quarter to affect sales in that quarter of the following year, but found few significant effects.

$$\Delta \ln S_{it} = \alpha_i + \quad Z_{it}'\delta + \quad + \sum_{s=0}^{1} \beta_{1is} [Q_{1t-s} * HDDV_{t-s}] + \sum_{s=0}^{1} \beta_{2is} [Q_{2t-s} * CDDV_{t-s}]$$

$$+ \sum_{s=0}^{1} \beta_{3is} [Q_{3t-s} * CDDV_{t-s}] + \sum_{s=0}^{1} \beta_{4is} [Q_{4t-s} * HDDV_{t-s}] + \varepsilon_{it} \qquad (17)$$

where S_{it} is nominal retail sales in category i at time t, $HDDV_t$ is the deviation in heating degree days, $CDDV_t$ is the deviation in cooling degree days, Q_{1t}-Q_{4t} are dummy variables equal to one for the first through fourth quarters, and Z_t is the vector of other factors that may affect spending. As before, the other determinants of spending are taken to be the log change in real labor income, the percent change in real stock prices, the change in the level of real interest rates, and the dependent variable, all lagged four times. Again, the estimation period is 1967:Q1 through 1998:Q4.

Table 5 shows the explanatory power of the weather variables in the quarterly models. The incremental R-squareds of the weather variables are fairly modest, for example, 3.4 percent for total retail sales. Still, the weather variables taken together are often jointly significant.

Table 6 shows results on the quarterly patterns. For several categories of stores, a cold first quarter is associated with significantly lower sales in that quarter and higher sales in the subsequent quarter. This pattern shows up for building material and supply stores, furniture and appliance stores, other durable goods outlets, general-merchandise stores, and restaurants, and for the GAF category more generally. However, the sum of coefficients is never significant at conventional levels, implying that the second-quarter bounceback tends to offset the first-quarter lull. This suggests some tendency to defer shopping when the weather is cold, and then make up for lost time in the subsequent quarter.

For the second quarter, there is a bit of evidence of the common view that a warm spring boosts spring sales but leads to a weak summer -- however, this pattern is significant for general-merchandise outlets only. A warm Q2 appears to raise spending at restaurants during that quarter, with no significant decline in spending during the subsequent quarter. For several types of stores -- furniture and appliance, food, and apparel -- unusually warm weather in Q2 has no significant effect on spending during that quarter, but is associated with significantly lower nominal spending in the subsequent quarter. I examined whether Q2's status as a "changeover" quarter might explain this result, using both heating and cooling degree days to measure "unusual weather" for Q2, but even with a number of refinements along these lines, the basic pattern still held up. Conceivably, the results may reflect effects via prices and the composition of sales: for example, a warm spring may lead to strong prices for spring/summer merchandise but discounting of winter/transitional merchandise, followed by slow sales and markdowns of spring/summer merchandise in the summer.[14]

For the third quarter, there is no evidence that a warm summer has any systematic effect in driving people to the malls: none of the coefficients on the Q3 weather variables are statistically significant. This is in contrast to results from the monthly models, which showed higher retail sales in unusually warm months followed by lower sales thereafter. This suggests that hot weather may have appreciable influence on the *timing* of sales during the summer, but that *total* sales are not systematically higher when the summer is unusually warm.

Finally, results for the fourth quarter show some tendency for cold Q4 weather to be followed by strong sales in Q1, although the weather variables have no significant effect in Q4 itself. The net effect is positive and significant for total retail sales; there are also positive net effects at a 10% level or better for several categories of nondurable goods (general merchandise, apparel, and restaurants). Again, the interpretation of these results is difficult without knowing about movements in prices and the composition of sales. It seems possible, however, that the lack of a significant effect in Q4 may be due to holiday gift-giving, with people more likely to

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[14]There are no high-frequency data on the product composition of sales. The Bureau of Economic Analysis releases monthly data on real personal consumption expenditures by product category. However, as Wilcox (1992) points out, "the information content of the PCE and retail-sales estimates [for spending on goods other than motor vehicles] is essentially the same, because the PCE estimates are calculated as fixed linear combinations of the retail-sales data." Also, most of the monthly and quarterly estimates of spending on services are based on judgmental trends. See U.S. Department of Commerce (1990).

brave the elements to satisfy seasonal shopping obligations.

5. Summary and discussion.

In sum, there are significant effects of unusual weather on nominal retail sales. The monthly data show considerable evidence of weather-related dips followed by swings, or vice versa. For durable goods, unusually cold weather sometimes leaves sales a bit up on net, possibly reflecting replacement-demand for items damaged or worn down in poor weather. In the quarterly data, there is some evidence of weather sensitivity for department store sales, along with a tendency for sales to slump in a cold first quarter and then bounce back in the second. But there are few other effects in the quarterly data, and the explanatory power associated with the weather variables is generally quite modest.

Thus, weather is indeed important for monthly fluctuations in retail sales, although the monthly effects tend to be offsetting and largely wash out at a quarterly frequency. These findings are consistent with a model in which weather affects the productivity of time in non-market activities, shifting the demands for goods; they may also reflect effects via retailers' incentives to clear inventories. However, without related data on prices or physical quantities of goods, it is hard to determine with any precision the relative importance of such effects.

Table 1. **Average share of annual sales, by month, for different types of retail establishments**

	Average share of annual sales											
	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.
Total	7.18	7.00	8.01	8.11	8.51	8.49	8.38	8.55	8.19	8.56	8.65	10.38
Durable goods outlets	6.84	6.98	8.19	8.35	8.86	8.98	8.65	8.70	8.32	8.60	8.29	9.22
Auto dealers	6.97	7.29	8.69	8.69	9.08	9.22	8.84	8.72	8.28	8.58	7.97	7.67
Bldg mat. & supplies	6.02	6.04	7.46	8.57	9.53	9.53	9.23	9.25	8.93	9.16	8.28	7.99
Furniture & appl.	7.34	7.05	7.81	7.61	7.95	8.15	8.18	8.48	8.25	8.55	9.18	11.45
Other durable goods	6.65	6.53	7.17	7.38	8.04	8.09	7.64	8.24	7.90	8.13	8.81	15.44
Nondurable goods stores	7.28	7.01	7.94	7.94	8.35	8.23	8.26	8.55	8.15	8.52	8.86	10.91
Gen'l merchandise	5.85	5.89	7.35	7.60	8.10	7.89	7.53	8.26	7.78	8.42	10.06	15.28
Food stores	7.87	7.44	8.19	8.04	8.51	8.41	8.65	8.59	8.26	8.45	8.39	9.21
Gas stations	7.65	7.22	7.95	8.08	8.55	8.69	8.92	8.93	8.42	8.65	8.40	8.56
Apparel	6.35	6.01	7.65	7.97	8.03	7.78	7.49	8.61	8.14	8.52	9.33	14.12
Restaurants	7.28	7.11	7.99	8.13	8.69	8.77	8.97	9.20	8.49	8.66	8.19	8.53
Other nondurable goods	8.09	7.81	8.22	7.84	8.00	7.66	7.61	7.86	7.87	8.61	9.11	11.35
Memo item: GAF category	6.30	6.17	7.52	7.69	8.05	7.92	7.66	8.39	7.97	8.47	9.70	14.18

Source: Author's computations, U.S. Bureau of the Census, Monthly Retail Trade Survey, 1967-1998.

Table 2. **Explanatory power of weather variables, monthly model**

	HDD		CDD		HDD & CDD	
	Incr. R^2	Joint sign.	Incr. R^2	Joint sign.	Incr. R^2	Joint sign.
Total retail sales	0.094	0.000	0.039	0.045	0.097	0.000
Durable goods outlets	0.063	0.000	0.021	0.370	0.061	0.000
Auto dealers	0.028	0.001	0.006	0.546	0.024	0.007
Bldg mat. & supplies	0.184	0.000	0.028	0.150	0.185	0.000
Furniture & appl.	0.057	0.000	0.020	0.166	0.055	0.001
Other durable	0.029	0.007	0.006	0.075	0.036	0.009
Nondurable goods	0.056	0.002	0.037	0.067	0.060	0.004
Gen'l merchandise	0.213	0.000	0.178	0.011	0.227	0.000
Food stores	-0.005	0.799	0.001	0.146	-0.002	0.179
Gasoline	0.009	0.129	0.002	0.239	0.011	0.113
Apparel	0.047	0.000	-0.005	0.449	0.045	0.000
Restaurants	0.139	0.000	-0.001	0.265	0.144	0.000
Other nondurable	0.071	0.000	-0.006	0.619	0.068	0.000
Memo: GAF category	0.183	0.000	0.116	0.034	0.189	0.000

Table 3. **Estimated effects of deviations in heating degree days, monthly models**

	β_t	β_{t-1}	β_{t-2}	β_{t-3}	Sum	Sign.
Total retail sales	-0.028*	0.047*	0.016+	0.010	0.045	0.008
	(3.42)	(5.39)	(1.65)	(1.03)		
Durable goods outlets	-0.057*	0.088*	0.033	0.013	0.077	0.027
	(3.12)	(4.67)	(1.59)	(0.70)		
Auto dealers	-0.051+	0.118*	0.027	0.001	0.096	0.050
	(1.83)	(3.94)	(0.95)	(0.05)		
Bldg mat. & supply	-0.109*	0.091*	0.068*	0.016	0.066	0.055
	(4.38)	(3.97)	(3.05)	(0.76)		
Furniture & appl.	-0.033*	0.026*	0.013	0.042*	0.048	0.056
	(2.04)	(1.98)	(0.83)	(3.31)		
Other durable	-0.056*	0.027	0.050*	0.013	0.035	0.303
	(2.45)	(1.34)	(2.17)	(0.77)		
Nondurable goods	-0.013+	0.023*	0.010	0.002	0.022	0.051
	(1.69)	(3.52)	(1.40)	(0.30)		
General merchandise	-0.051*	0.021	0.022+	0.031*	0.023	0.191
	(4.53)	(1.47)	(1.91)	(2.54)		
Food stores	0.001	0.010	0.001	0.004	0.015	0.334
	(0.06)	(1.05)	(0.09)	(0.44)		
Gas stations	0.028*	0.009	0.012	-0.014	0.035	0.140
	(2.13)	(0.60)	(0.98)	(0.90)		
Apparel	-0.068*	0.048*	0.007	0.013	-0.000	0.999
	(3.87)	(3.17)	(0.45)	(0.89)		
Restaurants	-0.053*	0.065*	0.020*	-0.009	0.022	0.194
	(4.56)	(4.94)	(1.99)	(0.96)		
Other nondurable	0.054*	0.004	-0.023*	-0.015	0.019	0.244
	(4.89)	(0.34)	(2.39)	(1.62)		
Memo: GAF category	-0.052*	0.029*	0.017	0.030*	0.024	0.157
	(5.13)	(2.64)	(1.45)	(2.86)		

*=Significant at a 5 percent level.
+=Significant at a 10 percent level.

Notes: Estimated coefficients are multiplied by 1000 to facilitate comparisons. T-statistics in parentheses. Hypothesis tests were conducted using a heteroskedasticity- and serial-correlation-robust covariance matrix, allowing serial correlation at lags up to 4.

Table 4. **Estimated effects of deviations in cooling degree days (monthly model)**

	β_t	β_{t-1}	β_{t-2}	β_{t-3}	Sum	Sign.
Total retail sales	0.071*	-0.074*	0.015	0.032	0.043	0.397
	(2.45)	(2.14)	(0.40)	(0.97)		
Durable goods outlets	0.100	-0.132	0.086	0.028	0.081	0.465
	(1.48)	(1.60)	(0.97)	(0.41)		
Auto dealerships	0.137	-0.162	0.124	0.028	0.128	0.461
	(1.29)	(1.23)	(0.88)	(0.25)		
Bldg mat. & supply	0.063	-0.102+	0.094+	-0.005	0.050	0.525
	(1.09)	(1.91)	(1.76)	(0.10)		
Furniture & appl.	0.065	-0.088*	0.049	-0.041	-0.015	0.802
	(1.58)	(2.37)	(1.02)	(0.97)		
Other durable	0.021	-0.047	-0.092+	0.153*	0.034	0.682
	(0.41)	(0.90)	(1.79)	(2.53)		
Nondurable goods	0.052*	-0.029	-0.032	0.024	0.015	0.665
	(2.32)	(1.42)	(1.59)	(1.16)		
Gen'l merchandise	0.130*	-0.108*	0.026	0.021	0.070	0.239
	(3.21)	(2.80)	(0.66)	(0.63)		
Food stores	0.051+	0.011	-0.048+	0.006	0.020	0.636
	(1.67)	(0.39)	(1.82)	(0.22)		
Gas stations	0.044	-0.080+	-0.024	0.036	-0.024	0.641
	(1.16)	(1.86)	(0.56)	(0.98)		
Apparel	0.024	-0.032	0.004	0.074+	0.069	0.377
	(0.46)	(0.68)	(0.09)	(1.80)		
Restaurants	0.023	0.011	-0.067*	0.017	-0.017	0.732
	(0.73)	(0.41)	(2.26)	(0.51)		
Other nondurable	-0.002	-0.008	-0.018	0.045	0.016	0.768
	(0.09)	(0.33)	(0.53)	(1.29)		
Memo: GAF	0.092*	-0.088*	0.025+	0.021	0.050	0.345
	(2.57)	(2.64)	(0.66)	(0.71)		

*=Significant at a 5% level.
+=Significant at a 10% level.

Notes: Estimated coefficients are multiplied by 1000 to facilitate comparisons. T-statistics in parentheses. Hypothesis tests were conducted using a heteroskedasticity- and serial-correlation-robust covariance matrix, allowing serial correlation at lags up to 4.

Table 5. **Explanatory power of weather variables, quarterly models**

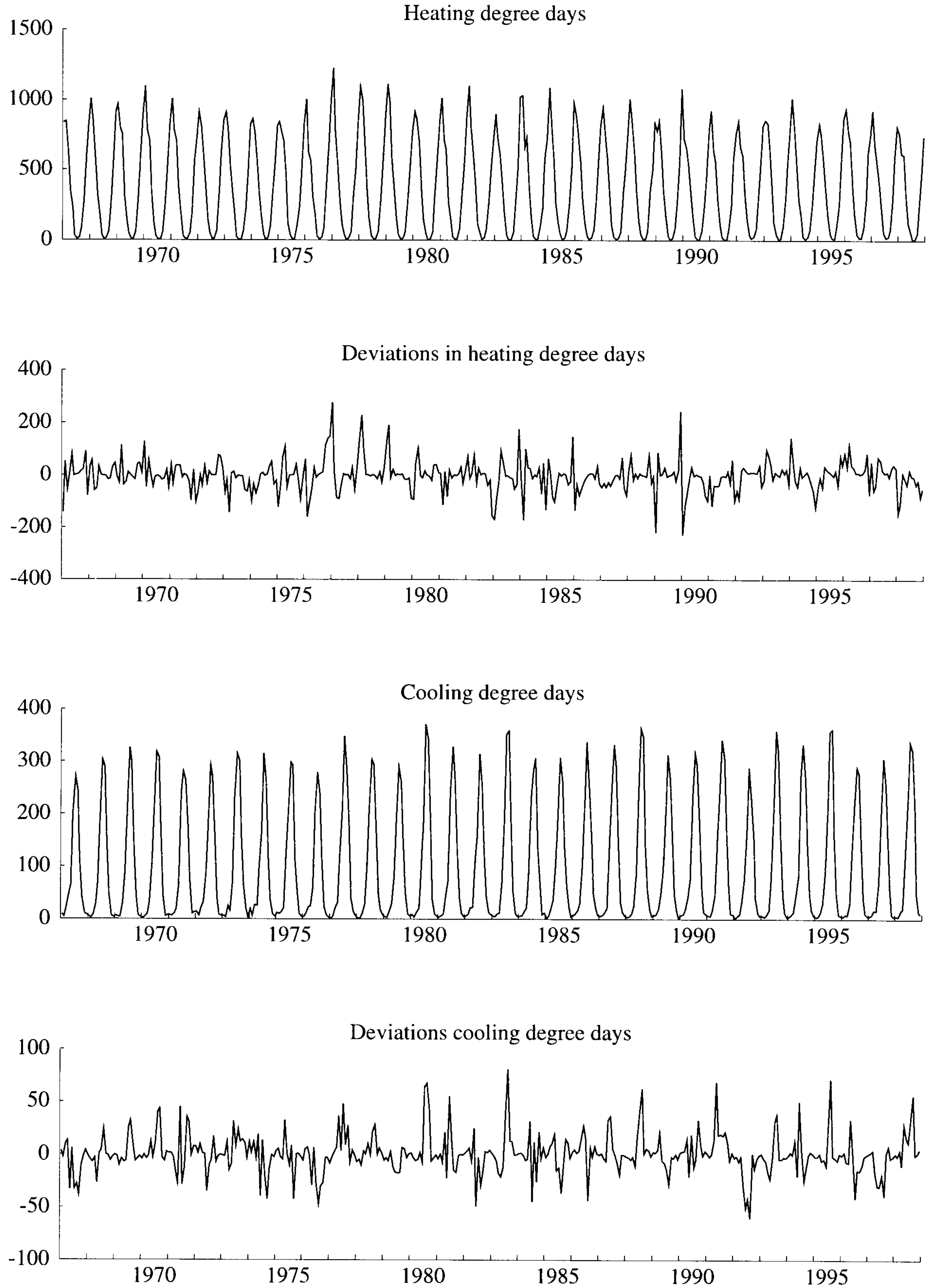
	Incr. R^2	Joint sign.
Total retail sales	0.034	0.004
Durable goods outlets	-0.020	0.110
Auto dealers	-0.034	0.150
Bldg mat & supply	0.193	0.014
Furniture & appl.	0.093	0.000
Other durable	0.196	0.001
Nondurable goods stores	0.075	0.000
Gen'l merchandise	0.150	0.007
Food stores	0.006	0.001
Gas stations	-0.031	0.525
Apparel	0.053	0.000
Restaurants	0.165	0.000
Other nondurable	0.097	0.000
Memo item: GAF category	0.163	0.001

Table 6. **Estimated effects of unusual weather, quarterly models**

	Q_1*HDDV				Q_2*CDDV				Q_3*CDDV				Q_4*HDDV			
	β_t	β_{t-1}	Sum	Sign.	β_t	β_{t-1}	Sum	Sign.	β_t	β_{t-1}	Sum	Sign.	β_t	β_{t-1}	Sum	Sign.
Total retail sales	-0.05+	0.09	0.04	0.50	0.21	-0.19	0.02*	0.93	-0.02	0.10	0.08	0.62	0.04	0.15*	0.19*	0.01
	(1.79)	(1.58)			(1.02)	(1.11)			(0.13)	(0.96)			(0.72)	(3.74)		
Durable goods outlets	-0.09	0.20	0.12	0.31	0.43	-0.03	0.39	0.54	-0.14	0.15	0.01	0.98	0.01	0.27*	0.28	0.16
	(1.24)	(1.79)			(0.93)	(0.08)			(0.46)	(0.60)			(0.07)	(2.57)		
Auto dealers	0.01	0.21	0.23	0.17	0.64	0.23	0.87	0.35	-0.30	0.11	-0.20	0.72	-0.00	0.37*	0.36	0.22
	(0.13)	(1.52)			(0.99)	(0.40)			(0.72)	(0.29)			(0.02)	(2.24)		
Building mat & supply	-0.19*	0.37	0.18	0.18	0.47	-0.25	0.22	0.66	0.13	0.13	0.26	0.40	0.10	0.12	0.22	0.25
	(2.34)	(3.37)			(1.10)	(0.74)			(0.59)	(0.71)			(0.79)	(1.10)		
Furniture & appl.	-0.12*	0.19	0.07	0.38	0.11	-0.62*	-0.51	0.15	0.28	-0.12	0.16	0.56	-0.04	-0.00	-0.04	0.78
	(2.36)	(3.52)			(0.44)	(2.53)			(1.58)	(0.58)			(0.42)	(0.00)		
Other durable	-0.21*	0.23	0.03	0.67	-0.01	-0.37	-0.38	0.29	0.12	0.07	0.18	0.39	-0.01	0.09	0.08	0.33
	(4.29)	(3.78)			(0.05)	(0.57)			(0.75)	(0.49)			(0.09)	(1.32)		
Nondurable goods stores	-0.03	0.03	0.00	0.97	0.08	-0.27*	-0.19	0.24	0.03	0.02	0.05	0.56	0.04	0.06*	0.10*	0.01
	(1.36)	(1.05)			(0.63)	(2.78)			(0.52)	(0.34)			(1.97)	(2.17)		
Gen'l merchandise	-0.10*	0.05	-0.05	0.37	0.42*	-0.31*	0.11	0.54	0.12	0.14	0.26	0.11	0.03	0.07	0.10+	0.09
	(3.09)	(1.19)			(2.79)	(2.27)			(1.04)	(1.40)			(0.63)	(1.62)		
Food stores	0.03	0.02	0.06	0.10	0.04	-0.23*	-0.19	0.20	0.07	-0.02	0.05	0.34	0.06*	0.02	0.08	0.13
	(1.20)	(0.92)			(0.34)	(3.29)			(1.35)	(0.34)			(2.28)	(0.46)		
Gas stations	0.04	0.09	0.13	0.41	-0.24	-0.48	-0.72	0.19	0.02	0.07	0.08	0.72	0.05	0.16	0.22	0.10
	(0.55)	(0.88)			(0.64)	(1.43)			(0.07)	(0.37)			(0.54)	(1.14)		
Apparel	-0.10*	-0.01	-0.11	0.20	0.03	-0.49*	-0.46*	0.04	0.09	0.30*	0.39	0.05	0.12	0.06	0.18*	0.03
	(2.12)	(0.13)			(0.14)	(3.13)			(0.82)	(2.08)			(1.68)	(0.81)		
Restaurants	-0.09*	0.05	-0.03	0.52	0.55*	-0.21	0.35	0.16	0.12	-0.25+	-0.13	0.40	-0.08	0.24*	0.16+	0.09
	(2.37)	(1.72)			(3.56)	(1.27)			(1.36)	(1.88)			(0.99)	(4.38)		
Other nondurable	0.04	-0.05	-0.02	0.70	-0.26	0.06	-0.20	0.34	0.03	0.26*	0.29*	0.01	0.14*	-0.09*	0.05	0.38
	(1.40)	(1.63)			(1.44)	(0.48)			(0.48)	(2.57)			(3.91)	(2.40)		
Memo item: GAF	-0.11	0.07	-0.04	0.55	0.25	-0.40	-0.16	0.39	0.13	0.13	0.26	0.12	0.04	0.05	0.09	0.14
	(3.44)	(1.43)			(1.57)	(3.07)			(1.22)	(1.27)			(0.83)	(1.09)		

* = significant at a 5% level.
+ = significant at a 10% level.
Notes: Estimated coefficients are multiplied by 1000 to facilitate comparisons. T-statistics in parentheses. Hypothesis tests were conducted using a heteroskedasticity- and serial-correlation-robust covariance matrix, allowing serial correlation at lags up to 4.

Figure 1. Measures of average temperatures



Appendix. **Distribution of retail sales across different types of establishments, 1998**

	Types of establishments included	Share of total sales (%)
Durable goods stores		
Automotive dealers	New and used motor vehicle dealers; boat, RV, and motor cycle dealers; auto and home supply stores (tires, batteries, parts, and accessories)	24.5
Building material & supply	Lumber yards; paint & hardware stores; nurseries, garden and lawn supply stores; mobile home dealers	6.1
Furniture and appliances	Furniture, home furnishings, and household appliance stores; radio, TV and computer stores; music stores.	5.9
Other durable goods	Sporting good and bicycle stores; book stores; jewelry stores; camera stores; luggage stores.	5.5
Nondurable goods stores		
General merchandise	Department stores (conventional, discount, and national chain); variety stores; misc. general merchandise stores.	13.1
Food group	Grocery stores; meat and fish (seafood) stores; retail bakeries; fruit stores and vegetable markets; candy, nut and confectionary stores.	16.4
Gasoline service stations	Establishments primarily selling gasoline and lubricants (may also sell tires, batteries, and convenience items, or repair services)	5.5
Apparel and accessories	Men and boys, women's, family clothing stores, shoe stores, misc. accessories	4.6
Restaurants	Restaurants; lunchrooms, cafeterias; refreshment places; drinking places	9.1
Other nondurable	Drug and proprietary stores; liquor stores; fuel dealers; florists; stationery stores; news dealers and newsstands; nonstore establishments (including mail order); misc. other.	9.3
General merchandise, apparel, furniture and appliances (GAF)	Sales at all stores in these categories.	23.6

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