Liquidity, Activity, Mortality

William N. Evans
Department of Economics and Econometrics
University of Notre Dame
440 Flanner Hall
Notre Dame, IN 46556
Vmail: 574 631 7039
Email: wevans1@nd.edu

Timothy J. Moore
Department of Economics
University of Maryland
Tydings Hall
College Park, MD 20742
Vmail: 301-442-1785
Email: moore@econ.umd.edu

December 19, 2008

Abstract

We document a within-month mortality cycle where deaths decline before the first of the month and then spike after the first. This cycle is present for a wide array of causes of death and many demographic groups. In contrast to the previous literature on this subject, we demonstrate the cycle is not simply due to substance abuse. A similar monthly cycle exists for a variety of activities such as movie attendance, visits to malls and consumer purchases, suggesting the mortality cycle may also be due short-term variation in levels of activity. We provide evidence that the within-month activity cycle is generated by liquidity. First, the within-month consumption and mortality cycles are greatest for demographic groups we a priori would expect to have liquidity problems at the end of the month. Second, amongst seniors, consumption and mortality peak after the arrival of Social Security checks. Third, the single largest within-month consumption cycle is for one of the few legal products that must be purchased with cash – lottery tickets. Our results suggest a causal pathway where liquidity problems reduce activity, which in turn reduces mortality. These relationships help explain the pro-cyclic nature of mortality. The death categories with the largest peak-to-trough over the month are the same causes of death most tied to the business cycle.

We wish to thank Ron Mariutto, Jon Skinner, Craig Garthwaite, Dan Hungerman, and James Sullivan for a number of helpful suggestions, as well as seminar participants at the University of Notre Dame, University of Indiana – Bloomington, Dartmouth, University of Maryland – College Park, and the University of Chicago.

I. Introduction

The average number of deaths changes over the course of a calendar month. As has been documented in medicine (Phillips, Christenfeld and Ryan, 1999), there is a drop of nearly 1 percent in the average mortality in the week prior to the first of the month and an equally large increase in mortality in the first week of the month. This within-month mortality cycle is particularly pronounced for homicides, suicides and accidents.

Phillips, Christenfeld and Ryan speculate that this within-month cycle may be driven in part by substance abuse. They note that these causes of death are often associated with substance abuse and "money for purchasing drugs or alcohol tends to be available at the beginning of the month and is relatively less available (for people with low incomes) at the end of the month." Subsequent work examining this cycle has focused on the role that a sudden infusion of cash has on substance abuse, a link that is often referred to as the 'full wallets' hypothesis (Rosenheck et al., 2000; Swartz, Hsieh and Baumohl, 2003; Maynark and Cox, 2000; Riley et al., 2005; Riddell and Riddell, 2005; Dobkin and Puller, 2007).

In this paper, we demonstrate that the within-month mortality cycle is a more general phenomenon that extends well past substance abuse. Although the peak-to-trough in the within-month cycle is large in percentage terms for substance abuse deaths, these represent a small fraction of total deaths and account for a minority of the overall pattern. Updating and extending the earlier work of Phillips Christenfeld and Ryan, we document a within-month mortality cycle for many causes of death, including external causes, heart disease, heart attacks, and stroke, but not for other causes such as cancer and leukemia. The pattern is also evidence for all age groups, both sexes, all races, for all marital status groups, for urban and rural residents, and for people in all education groups. We also find that the pattern is evident for deaths not related to substance abuse. These patterns remain after controlling for special days in the calendar that occur at a particular time in a month, such as New Year's Day and Independence Day.

The broad-based nature of the within-month mortality cycle leads us to examine whether these cyclic patterns are present in the levels of different activities. To that end, we obtained daily data on a number of different activities and purchases, including going to the mall, visiting retail establishments, purchasing lottery tickets, going go the movies, and amounts spent on food and non-food retail purchases. These data all show the same pattern, namely, that activity declines before the start of the month and rebounds after the first of the month. This set of results is consistent with research on the 'excess sensitivity' of consumption to the arrival of expected income payments, models which typically have been used to test the life cycle/permanent income hypothesis. According to this hypothesis, predictable changes in income should have no effect on consumption once the income is actually received. The life-cycle/permanent income hypothesis has been rejected in a number of contexts where authors have demonstrated that consumption rises when predictable changes in income are realized, such as when where consumers demonstrate excess sensitivity including predictable changes in income (e.g. Wilcox, 1989; Parker, 1999; Souleles, 1999). Our work is most similar to that of Stephens (2003), who found an increase in consumption of time-sensitive purchases like perishable food and eating out at restaurants among seniors after the receipt of Social Security checks on the third of the month. This within-month consumption cycle has been interpreted by some as an example of hyperbolic discounting (Shapiro, 2005; Mastrobuoni and Weinberg, 2007).

The concordance between the mortality and activity cycles leads us to conclude that it is activity that leads to mortality. For some causes of death, this link is obvious: one cannot die in a traffic accident unless one is in traffic. As activity declines and then increases around the first of the month, it becomes natural for such causes of death to demonstrate the same pattern. The link between activity and other causes of death is not as obvious but is well-documented in the medical literature. Triggers for heart attacks include getting out of bed in the morning (Elliott, 2000), going back to work on Mondays (Witte et al. 2005; Willich et al. 1994), shoveling snow (Franklin et al, 1996; Heppell et al. 1991), the busy Christmas season (Phillips et al. 2004), having sex (Moller et al. 2001), a heavy meal (Lipovetsky et al. 2004), watching your favorite sports team lose (Witte et al., 2000; Kirkup and Merrick, 2003), and physical exertion (Lipovetsky et al. 2004; Albert et al. 2000). Similar triggers have been documented for strokes as well. In the same way, our results suggest a rise in activity after the first of the month is responsible for the rise in mortality.

We provide suggestive evidence that the rise in mortality is linked to changing liquidity over the month. First, we document that the peak-to-trough in mortality is greatest for those with low levels of education, a group that has been found to have the greatest liquidity problems. Second, we demonstrate the peaks in elderly mortality and consumption are just after the arrival of Social Security payments, and the pattern changes when the timing of these payments change. Third, we also link liquidity to movements in consumption by showing there are smaller movements in activity and consumption over the month for groups we would expect to have less liquidity issues, namely, those in higher-income groups and those with more education. Fourth, of all the goods and activities we examine, the largest swing in consumption is for lottery tickets: a good that can only be purchased with cash in many states.

This examination of the broader relationship between liquidity, activity and mortality has implications for a growing literature on mortality over the business cycle. A voluminous literature with contributions from a variety of disciplines has established that health outcomes are much better among individuals with higher socioeconomic status. In contrast to this work is a more recent strand of literature documenting that mortality is pro-cyclic. The basic statistical relationship has been documented for the United States (Ruhm, 2000) and verified in a number of other countries as well. What has been missing from this literature is an explanation for the procyclicality of mortality that reconciles it with the protective role of income. The relatively short cycle of a month enables a distinction to be made between transitory income changes and permanent income levels. To see whether a possible explanation for the procyclicality of mortality is that fluctuations in income over the business cycle change activity levels and mortality outcomes, in the final section of the paper we document that the death categories with the greatest peak-to-trough within-month mortality cycle are also those death categories most strongly tied to the business cycle. This suggests that rising mortality in a boom is a function of greater activity generated by a robust and healthy economy.

II. The Within-Month Mortality Cycle

In a 1999 paper in the *New England Journal of Medicine*, Phillips, Christenfeld and Ryan use data on all deaths in the United States between 1973 and 1988 to identify a within-month mortality cycle.[1] Looking at the fourteen days prior to the first of the month and the fourteen days after the first of the month, the authors find daily deaths decline as the first of the month approaches and spike to above-average levels after the first of the month. This within-month mortality cycle is particularly pronounced for homicides, suicides, traffic accidents and other external causes.

With government transfers generally paid at the beginning of each month, the authors speculate that this within-month cycle is primarily due to an interaction of liquidity constraints and when alcohol and drugs are consumed. They identify deaths whose primary or secondary cause of death is related to the use of alcohol or drugs other than tobacco, and find a striking pattern. All deaths are about one percent higher in the first week of the month compared to the week before. In contrast, substance abuse deaths are 14 percent higher during the first week of the month compared to the week before.

This pattern matches research into the relationship between the timing of government transfers and outcomes related to substance abuse. Verhuel, Singer and Christenson (1997) explore such patterns in British Columbia and find mortality, hospital admissions, admissions to drug and alcohol detoxification centers, and emergency medical responses increase the week after welfare checks are distributed. Using data for the state of Washington, Maynard and Cox (2000) demonstrate a higher rate of hospitalizations for substance abuse among Medicaid and non-Medicaid patients during the first week of the month. Halpern and Mechem (2001) find a greater within-month cycle in hospital admissions for psychiatric patients in the United States with a primary diagnosis of a substance abuse disorder, compared to other psychiatric patients. Riddell and Riddell (2006) find an increase in hospital discharges against medical advice among heroin addicts in Vancouver in the week after welfare checks were distributed, while Li et al. (2007) finds evidence of an increase in public drunkenness in Vancouver in the week after welfare checks are distributed. Finally, Foley (2008) finds a different monthly cycle for crimes motivated by

[1] Exact dates of death are only available on the 1973-1988 public use Multiple Cause of Death data files, which is why Phillips et al. (1999) restrict their analysis to those years.

financial gain, such as burglary, robbery and motor vehicle theft. In states where government transfers are primarily paid at the start of the month, these crimes increase in the week prior to the first of the month and then decline in the week after the first, a pattern he attributes to the same lack of liquidity towards the end of the month.

In the most detailed study to date, Dobkin and Puller (2007) use administrative records from California to show a pronounced within-month hospital admission cycle among Supplemental Security Income (SSI) and Social Security Disability Income (DI) recipients, with the peaks particularly pronounced for substance abuse admissions. Dobkin and Puller also demonstrate a large within-month mortality cycle for in-hospital deaths among SSI and DI recipients, but no in-hospital monthly cycle for the non-aged not on federal assistance programs.

Phillips, Christenfeld and Ryan (1999) note a smaller within-month mortality cycle is evident for deaths for which substance abuse is not mentioned as a primary or secondary cause. In none of the studies cited above, however, are explanations other than the interaction of welfare payments and substance abuse. In the sections below, we first update the Phillips, Christenfeld and Ryan analysis using data from 1973 to 2005. The pattern is still evident, and remains of a similar magnitude. Then, using a broader set of conditions related to substance abuse and all mentions of these conditions as a cause of death, we demonstrate that a focus on substance abuse deaths is too narrow. The results below suggest the within-month mortality cycle extends well past substance abuse deaths and encompasses many causes of death. More importantly, although the peak-to-trough for substance abuse deaths is large, its role in the aggregate within-month cycle is small. In contrast, although heart attacks have a much smaller within-month mortality cycle, the broad-based nature of this disease means the number of deaths in this category is large.

III. Replicating and Expanding the Basic Findings

a. Pooling Samples from 1973 -2005.

The primary data for this analysis are from the Multiple Cause of Death (MCOD) data files from 1973 through 2005. These files contain a unique record for each death within the United States. Data are compiled by states and reported to the National Center for Health Statistics (NCHS), which disseminates the data.[2] Exact dates of death were reported on public use data files starting in 1973, but with the redesign of the public use layout in 1989 this information was removed from public use files and is only available on restricted-use versions of the data.[3] Permission to use these restricted data was obtained from the NCHS. Combining the 1973-1988 public use files with the 1989-2005 restricted-use data provides us with information on over 71.5 million deaths, which we term our Pooled Mortality Sample.

The Pooled Mortality Sample contains detailed information about the decedent, including their age (in years), race, gender, place of residence and place of death. Starting in 1989, years of education is also included, which is usually provided by the next of kin. In 1989, 21 states reported an education for at least 90 percent of decedents but this number rises to 42 states by 1995 and 48 states by 2005.[4] The data files also contain detailed data on the multiple cause of death using various versions of the International Classifications for Diseases (ICD) classification. Specifically, ICD-8 was used from 1973 to 1978, ICD-9 was used between 1979 and 1998, and ICD-10 has been used since 1999. Assigning broad cause-of-death categories necessitated matching disease categories across the three versions, a process that is described in Appendix I.

A graph of deaths from all causes for the entire 1973-2005 period is shown in Figure 1, and represents the basic facts of the within-month mortality cycle. The horizontal axis represents the days in relation to the first of the month, with Day 1 being the first of the month. To provide symmetry in the graph, we only report the 14 days prior to the first of the month and the first 14 days of the month, a total of 336 (12*28) days per year. The height of the graph represents the relative risk of death on the particular day which is simply total deaths on a particular day divided by the average deaths per day. A

---

[2] The District of Columbia reported education for more than 90% of decedents every year except1989. Detailed information about the Multiple Cause of Death data files is available at the NCHS web site, http://www.cdc.gov/nchs/products/elec_prods/subject/mortmcd.htm .

[3] Available at the NCHS Research Data Center (NCHS/RDC), http://www.cdc.gov/nchs/r&d/rdc.htm.

[4] There is a concern about the accuracy of this variable. Sorlie and Johnson (1996) note than when death certificates are matched to survey data obtained prior to death, the former match the latter in about 70% of the cases but on average, the death certificate data overstates reported education.

value of 1.1 would represent a 10 percent increase in the risk of death on that particular day. The relative risk is represented by the hollow circles, while the vertical lines from the circles are 95 percent confidence intervals.[5]

The basic shape of the graph is similar to that in Phillips, Christenfeld and Ryan (1999).[6] Starting about twelve days before the first of the month, daily deaths decline slowing, and fall to 0.8 percent below average deaths the day before the first of the month. Deaths then increase on the first of the month to 0.6 percent above average. The peak-to-trough represents about a 1.4 percent difference in daily mortality rates. In 2005, there were 2,448,017 deaths in the United States, or roughly 6,700 deaths per day. The current increase in deaths from the day before the first of the month to the first day of the month represents about 94 deaths per month, or about 1,100 deaths per year.

This within-month mortality cycle remains once we control for a set of covariates in a regression similar in structure to that in Stephens (2003). Let Y_{dmy} be counts of deaths for day *d* in month *m* and year *y*. In this case days are organized in relation to the first of the month, so *d* goes from -14 to 14. Months do not follow the calendar; instead they are a collection of 28 days surrounding the first of the month. *Month 1* contains data from December 18 through to January 14 of the next year, *Month 2* from January 18 through to February 14, and so on. Given this structure for the data, the econometric model we estimate is of the form:

$$(1) \qquad \ln(Y_{dmy}) = \alpha + \sum_{\substack{d=-14 \\ d\neq -1}}^{14} Day_d \beta_d + \sum_{j=1}^{6} Weekday(j)_{dmy}\gamma_j + \sum_{j=1}^{M} Special(j)_{dmy}\varphi_j + \mu_m + v_y + \varepsilon_{dmy}$$

Where Day_d is a dummy variable that equals 1 if it is day *d* and zero otherwise, *Weekday(j)* is one of six dummy variables for the different days of the week, *Special(j)* is one of *J* dummy variables that capture

[5] We use the delta method to construct the variance of the risk ratio. The variance of daily deaths is calculated as follows. Let N_t be the number of people alive at the start of day t, and the probability of death that day equal p_t. Since this is a set of Bernoulli trials, expected deaths (d_t) is $E[d_t] = N_t p_t$, and the variance of deaths is $V[d_t]=N_t p_t(1-p_t) = \sigma^2_t$. A consistent estimate of p_t is d_t/N_t. The risk of death on any single day is extremely low, such that $1-p_t$ is functionally one. Therefore an estimate of the variance of daily deaths is simply d_t.

[6] Using data from 1973-1988 only, we are able to replicate the basic results in the original Phillips, Christenfeld and Ryan paper.

special days throughout the year such as New Year's Day and Christmas.[7] The variables μ_m and v_y capture synthetic month and year effects[8] and ε_{dmy} is an idiosyncratic error term. In this equation, the reference day is day prior to the start of the month (i.e. *Day -1*) and the reference weekday is Saturday. We anticipate the data exhibits autocorrelation but because our time series only has 336 observations per year, the holes in the sample make any standard autocorrelation correction difficult to implement. Therefore, we estimate standard errors allowing for arbitrary correlation within the 28 days of the synthetic month.[9]

In Table 1, we report estimates for the coefficients representing the days of the month from two separate equations. The first model is a regression of the natural log of the fatality counts on the 27 dummy variables for the day of the synthetic month (-14, -13, etc.), and no other covariates. This estimate is an empirical analog to the graphical presentation in Figure 1, and the coefficients show a steady decline in fatality counts prior to the first of the month and then a sharp increase on *Day 1*. Fatality counts peak on *Day 1* and *Day 4*, at 1.3 percent higher than on *Day -1*. The coefficients for the first fourteen days of the month are positive and statistically significant at conventional levels.

In the second model we generate estimates from estimates of equation (1), controlling for synthetic month and year effects, days of the week, and the special days throughout the year. The results for this equation are also in Table 1. The parameter estimates in Models (1) and (2) are similar, with deaths on the first fourteen days of the month approximately 1 percent higher than the day prior to the first of the month (*Day -1*). These differences are statistically significant. The main difference between

[7] We include unique dummies for a long list of reoccurring special days, including for January 1st and 2nd, the Friday through Monday associated with the all federal holidays occurring on Mondays (Presidents' Day, Martin Luther King Jr Day since 1986, Memorial Day, Labor Day, Columbus Day), Super Bowl Sunday and the Monday afterwards, Holy Thursday through Easter Sunday, July 4th, Veteran's Day, the Monday through Sunday of Thanksgiving, a dummy for all days from the day after Thanksgiving though New Year's Eve, plus single day dummies for December 24th through December 31st. We also reduce the number of homicides on September 11, 2001 by 2,902 deaths, which according to a Center for Disease Control report was the number of deaths on that date due to the terrorist attacks http://www.cdc.gov/mmwr/preview/mmwrhtml/mm51SPa6.htm. In models of fatality counts for specific demographic groups, such adjustments are not possible so we add a dummy variable for September 11, 2001.

[8] We have also estimated all models replacing the month and year effects with synthetic month -year effects, μ_{my}. The results with this alterative specification were virtually identical to the results from the more parsimonious specification.

[9] This implicitly assumes there is zero correlation in days across the months, which may be least correct for month 2 (January 18th through February 14th) and month 3 (February 15th through March 14) which is the only months in the sample that have adjacent days.

the models is that the regression-adjusted coefficient is substantially lower on *Day 1* than the unadjusted raw number. The regression adjustment reduces the coefficient on the *Day 1* dummy by about 20 percent. This is because New Year's Day is a high mortality day, with 17 percent more deaths than the daily average, the New Year's Day effect is eliminated form the analysis when we control for the special days.

The results in Table 1 show a definitive pattern where mortality declines before the first of the month and rebounds after the first. To better understand the magnitude of these results, we alter the model in equation (1) and estimate a model similar to those in Stephens (2003). Instead of including dummies for particular days, we estimate models with three weekly dummy variables: *Week -2* includes *Day -14* to *Day -8*, *Week 1* includes *Day 1* to *Day 7*, and *Week 2* includes *Day 8* to *Day 14*. The reference group is the week before the first of the month (*Week -1*, includes *Day -7* to *Day -1*), and therefore the coefficient on *Week 1* gives the percentage difference in daily mortality between the first week of the month and the preceding week.

Results for this model are reported in the top row of Table 2. Daily mortality is about 0.9 percent higher in the first week of the month than in the preceding week, and this result has an asymptotic t-statistic of about 5. With 5,938 deaths per day in our sample, over an entire year the first week of the month will generate roughly 4,324= (5,986*0.0086*7*12) more deaths than the last week of the month.

This relatively parsimonious specification can also be used to show that the mortality cycle is present for the fatality counts of a wide variety of demographic subgroups. The remaining rows of Table 2 contain the *Week -2*, *Week 1* and *Week 2* coefficients for groups divided by sex (male, female), race (white, black, other race), marital status (single, married, widowed, divorced), age (under 18 years, 18 to 39 years, 40 to 64 years, over 65 years) and location (metropolitan county, non-metropolitan county). The results indicate the breadth of the phenomenon: all groups have a coefficient on *Week 1* that is positive and statistically significant at conventional levels, with deaths at least 0.5 percent higher in the first week of the month relative to the previous week. The pattern is most pronounced for the non-white (i.e. black, other race) and working-age (i.e. 18 to 39 years, 40 to 64 years) subpopulations, as well as those who are single and divorced.

b. Does the Within-Month Mortality Cycle Extend Past Substance-Abuse Related Deaths?

As noted above, when it comes to understanding the within-month mortality cycle, the original paper and subsequent research have focused on the role that access to cash has on substance abuse deaths, where substance abuse is broadly defined as deaths associated with drug or alcohol use. In this section, we examine whether the within-month cycle extends past substance abuse by identifying deaths that lists a cause of death possibly due to substance abuse.

Causes of death in the MCOD files are defined using the International Classification of Disease (ICD) codes according to three different versions: ICD-8 (1973 to 1978), ICD-9 (1979 to 1998) and ICD-10 (1999 to 2005). Later in the paper, we demonstrate that we are able to define broad cause-of-death categories that span the three versions of the ICD codes. However, the specificity of the codes used to identify substance abuse varies a lot across the versions. In this section, we restrict our attention to data over the 20-year period when the ICD-9 coding system was in place.

Given our primary concern is to look at the mortality cycle for deaths unrelated to substance abuse, we err on the side of including too many deaths in the substance abuse category rather than too few. Our definition of substance abuse-related deaths is broader than Phillips, Christenfeld and Ryan along two dimensions. First, Phillips et al. use only the primary and secondary causes of death to identify substance abuse related causes. Each death record contains up to twenty separate causes of death, however, and we identify substance abuse death using all causes. Second, a larger set of ICD-9 codes is used to identify substance abuse.

Phillips et al. use as their definition of a substance abuse-related death those with a primary or secondary cause with the following ICD-9 codes: 291 (drug psychoses), 292 (alcohol psychoses), 303 (drug dependence syndrome), 304 (alcohol dependence), 305.0 and 305.2-305.9 (non-dependent abuse of drugs except for 305.1, tobacco abuse), 357.5 (alcoholic polyneuropathy), 425.5 (alcoholic cardiomyopathy), 535.3 (alcoholic gastritis) 571.0-571.3, (chronic liver disease and cirrhosis with mention of alcohol), 790.3 (excessive blood alcohol level), E860 (accidental poisoning by alcohol not elsewhere classified), 947.3 and E977.3 (alcohol-use deterrents), and 980 (toxic effect of alcohol). We identify substance abuse using these ICD-9 codes and codes from studies on the economic costs of substance abuse in the United States (Harwood, Fountain, and Livermore, 1998), Australia (Collins and Lapsley, 2002) and Canada (Single et al., 1999).[10]

The effects of adding more condition codes and looking at all mentions of these codes can be seen in the proportion of deaths we classify as substance abuse. Phillips et al. classify 1.7 percent of the deaths from 1973 to 1988 as related to substance abuse. Over a similar time period we classify 4.4 percent of deaths as due to substance abuse.

Figure 2 contains the relative daily mortality rates for deaths related to substance abuse (in Panel B) and deaths not related to substance abuse (in Panel A). Like Phillips et al., there is a large peak-to-trough for deaths related to substance abuse. For the four days prior to the first of the month, deaths are approximately 2 percent below the daily average, before increasing on *Day 1* to 4 percent above the average daily mortality rate. Panel B contains the results for deaths not related to substance abuse. There is a similar monthly cycle, although the magnitudes are not as large. The trough occurs on *Day -1* and the peak occurs on *Day 1*, with a more than 1 percent difference between the two. Only one of the point averages for the fourteen days prior to the first of the month lie above the average, and none of the point estimates for the fourteen days after the first of the month lie below the overall average. There is a pattern present is not caused by substance abuse.

[10] These additional ICD-9 codes are: 305.0 (Nondependent abuse of alcohol); 357.5 (Alcoholic polyneuropathy); 357.6 Polyneuropathy due to drugs); 425.5 (Alcoholic cardiomyopathy); 535.3 (Alcoholic gastritis); 571.0 (Alcoholic fatty liver); 571.1 (Acute alcoholic hepatitis); 571.2 (Alcoholic cirrhosis of liver); 571.3 (Alcoholic liver damage, unspecified); 760.7 (Alcohol and drugs affecting fetus or newborn); 779.5 (Drug withdrawal syndrome in newborns); 790.3 (Excessive blood level of alcohol); 965 (Poisoning by analgesics, antipyretics, and antirheumatics); 967 (Poisoning by sedatives and hypnotics); 968 (Poisoning by CNS muscle tone depressants); 969 (Poisoning by psychotropic agents); 970 (Poisoning by CNS stimulants); 980 (Toxic effects of ethyl alcohol); E850-E858 (Accidental poisoning by drugs, medicaments, and biologicals); E860 (Accidental poisoning by alcohol not elsewhere classified); E863 (Accidental poisoning by agricultural and horticultural chemical and pharmaceutical preparations other than plant foods and fertilizers); E935.0-E935.2 and E937-E940 (Opiates and other drugs causing adverse effects in therapeutic use); E980 (Poisoning by solid or liquid substances where cause is undetermined); 640, 641, 648.3, 656.5 (Pregnancy complications due to alcohol and drugs); 762.0-762.1,764-765 (Neonatal conditions due to alcohol and drugs); 962.1 (Anabolic steroid poisoning); E950.0-E950.5 (Suicide, self-inflicted poisoning by drugs or medicinal substances; E962.0 (Assault by drugs and medicinal substances). More details are in Appendix II.

These patterns persist once the pattern is estimated using the natural log of fatality counts regressed on weekly dummies and the various controls contained in equation (1). The first row of Table 3 contains the coefficients on the weekly dummies for all deaths occurring between 1979 and 1998 where the reference period is *Week -1*. The results for this limited sample are virtually identical to those for the full sample (in the first row of Table 2).

The results for substance abuse and non-substance abuse related deaths are in the third and fourth rows of Table 3. Substance abuse deaths are 3.0 percent higher the first week of the month compared to the previous week, while for non-substance abuse related deaths this number is 0.77 percent. Notice however that there is an average of 257 substance abuse deaths per day, so a 3 percent increase puts 647 more deaths per year in the first week of the month compared to the previous week. By comparison, deaths not related to substance abuse average 5,622 per day, so there are 3,636 more of these deaths per year in the first week of the month compared to the last. Therefore, although substance abuse deaths are more cyclic than other causes, of the excess deaths during the first week of the year, only 15 percent are due to substance abuse.

c. Disaggregating deaths into detailed causes

The breadth of this phenomenon can also be seen in the within-month mortality patterns for different causes of death, with the creation of fifteen subgroups based on primary cause of death and consistently defined across Versions 8, 9 and 10 of the International Classification of Disease.[11] There are four groups based on external causes (motor vehicle accidents, homicide, suicide, all other external causes) and four cancer-related groups (lung cancer, breast cancer, leukemia, other cancers). The remaining categories are heart attacks; heart diseases other than heart attack; alcohol-related cirrhosis;

[11] Each ICD version has several thousand individual codes, but the changes from version to version means only large death categories can be consistent throughout the sample. The exact mapping of deaths into disease categories is outlined in Appendix I.

cirrhosis not related to alcohol; chronic pulmonary obstructive disease (COPD); stroke; and a final category with all deaths not included in the previous fourteen groups.

The monthly patterns for all of these categories are shown in Figure 3. Panel A to Panel D include the relative daily mortality rates for the four external cause categories: motor vehicle accidents, suicide, murder and all other external causes, such as accidents and drowning. All have a dip before the first of the month and a spike on the first. The number of suicides peaks again on the 5th of the month, and the other three cause-of-death categories peak on the 4th. The magnitudes of the peak-to-trough patterns are 7 percentage points for motor vehicle accidents and suicide, 13 percentage points for murder and 8 percentage points for other external causes.

The external cause-of death categories are clearly connected to the role of substance abuse. More interesting is that the within-mortality is present in a number of the other cause-of-death categories. Panel E shows the pattern for deaths where the primary cause of death was a heart attack. Heart attack deaths increase by more than 2 percent from the day before the first of the month to the day after the first. Other heart disease, shown in Panel F, displays a pattern that is similar although the peak-to-trough is of a slightly smaller magnitude (around 1 percent). A similar decline in deaths prior to the first of the month and increase on the first is observed for COPD (Panel G) and stroke (Panel H), with average differences between deaths occurring on the first day of a month and the last day of the previous month of 1.8 percent for COPD and 1 percent for stroke. In all cases, the ranges of the 95 percent confidence intervals put the number of the deaths below the average rate in the last few days of the month and above the average in the first few days of the month. Although these patterns are not as stark as those for external causes, they represent evidence of a phenomenon that requires a more general reason than the use of drugs and alcohol.

The pattern is slightly different for cirrhosis. Alcohol cirrhosis deaths (Panel I) are above the average daily rate between the fourth and the fourteenth of the month, and peak 4 percent above the average on the ninth day of the month. Non-alcohol cirrhosis deaths (Panel J) exhibit a similar pattern, moving above the average on the fourth of the month and then peak approximately 3 percent above the average on the eighth day of the month. As short-term changes in cirrhosis are influenced by changes in liver toxicity, the lagged nature of this pattern is consistent with substance abuse and, more generally, more consumption early in the month (Cook and Tauchen, 1982).

Finally, Panels K to N contain deaths for different types of cancers. Breast cancer deaths (Panel K) and Leukemia (Panel L) exhibit no discernible pattern over the course of a month. There is a slight dip below the average prior to the first for lung cancer deaths (Panel M), but there is an equivalent dip in the first few days of the month, which differs from the general pattern. A similar pattern occurs for other cancers (Panel N). In general, however, there is little-to-no pattern amongst cancer deaths.

The regression-adjusted pattern for these specific causes of death is investigated using the same equation (1) model used throughout this section. The week-of-month coefficients are shown in Table 4. Focusing on the *Week 1* dummy, there are statistically significant increases in mortality during the first week for all causes of death except three cancer groups: lung cancer, breast cancer, and leukemia. We find a small within-month cycle for other cancers. The largest within-month cycles are (in order): suicides, homicides, COPD, alcohol cirrhosis, other cirrhosis and motor vehicle accidents. The percentage of each group's deaths we define as related to substance abuse is also shown in Table 4. Heart attacks, other heart disease, stroke, COPD and non-alcohol cirrhosis all display a within-month mortality cycle yet, even using a broad coding for substance abuse, 0.5 percent of less of the deaths in each of these categories are potentially related to substance abuse.

c. Results for Motor Vehicle Fatalities

One of the largest peak-to-troughs in the within-month mortality cycle is for mortality caused by traffic accidents. In this section, the National Highway Traffic Safety Administration's Fatality Analysis Reporting System (FARS) is used to look at this death category in detail. These data indicate alcohol involvement in fatal accidents, so we can explore the variation in alcohol involvement throughout the day to further consider the importance of this cofactor in creating the within-month mortality cycle. FARS is in many respects superior to the MCOD data because it records the date when an event that leads to death occurred, which is exactly what we want.

FARS is a census of deaths associated with motor vehicle crashes. Local law enforcement agencies are required by federal law to provide detailed data about each motor vehicle accident where a death occurs within 30 days of the accident. Accident investigators are required to record the blood alcohol concentrations of the involved drivers, pedestrians and cyclists. This is not done in many cases but for most observations, law enforcement officers do provide an estimate as to whether the drivers were drinking. Combining these two indicators, we can generate estimates of the fraction of accidents producing a fatality that have alcohol involvement. Between 1982 and 2006, the FARS indicate that 44.8 percent of fatal motor vehicle accidents have a driver, pedestrian or bicyclist involved in the accident who had been drinking.[12] Figure 4 shows that the fraction of fatal accidents with alcohol involvement varies markedly depending on the time of the day. The proportion of accidents with alcohol involvement peaks at 82 percent at 2:00am, declines monotonically to 11 percent at 9:00am, and then the fraction increases monotonically throughout the rest of the day.[13] If the within-month mortality cycle is driven primarily by changes in substance abuse and alcohol consumption at the end of the month, we should see stark differences in the within month mortality cycle for accidents that occur at different points in the day.

Figure 5 shows the within-month mortality cycles in 1975 to 2006 FARS data, for all traffic accidents (in Panel A) and at different times of the day: morning (6:00am – 9:59am) in Panel B; midday (10:00am – 3:59pm) in Panel C; evening (4:00pm – 7:49pm) in Panel D; night (8:00pm –11:59) in Panel E; and overnight (12:00am – 5:59am) in Panel F. This last panel displays a within-monthly pattern that is heavily influenced by the high number of motor vehicle deaths on January 1st, so in Panel G we re-do the graph for overnight motor vehicle fatalities excluding the 28 days around January 1st. In both graphs the deaths prior to the first of the month are 4 percent below the average, however the peak on the first decreases from 25 percent to 6 percent above the average after this adjustment.

[12] FARS documentation cautions users about the quality of the data in the early years and most official reports about alcohol involvement from the National Highway Traffic Safety Administration use data from 1982. For more information about FARS, see http://www.nhtsa.dot.gov/people/ncsa/fars.html. FARS data is available for download at ftp://ftp.nhtsa.dot.gov/fars/.

[13] The use of illicit drugs is not measured in FARS data and the prevalence of "drug driving" is not particularly well understood, however officer judgments as to driver impairment may partly take into account the effects of illicit drug use.

The percentage of accidents with alcohol involvement is high at night (66.6 percent) and overnight (73.1 percent), close to the average in the evening (42.7 percent), and much lower in the morning (15.7 percent) and midday periods (18.0 percent). Yet fatalities in all periods decline leading up to the first of the month and are above-average levels immediately after the first. The week-of-month regression-adjusted patterns for total motor vehicle fatalities and for the five different periods in the day are reported in Table 5. All periods show a within-month cycle, with positive and statistically significant *Week 1* coefficients. Interestingly, the peak deaths in the first week compared to the week prior to the start of the month is during the midday hours (10:00am – 4:00pm), even though less than 20 percent of fatal accidents had alcohol involvement at that time of the day. These results suggest that not all of the change in mortality is being driven by changes in alcohol use and abuse but rather, a more general phenomenon.

IV. Linking Mortality to Activity

In Figure 3 and Table 4, we demonstrate a within-month mortality cycle for a number of causes of death. As we note in Figure 2, and elsewhere in the previous section, in contrast to previous suggestions, the cycle cannot be explained fully with changes in substance abuse. Therefore, a more general explanation for the broad-based nature of the within-month mortality cycle is called for.

The specific causes of deaths that demonstrate the most cyclicality within the month help suggest a particular etiology. In particular, we suggest in this section that activity spurs on mortality for many causes of death and therefore, a drop in activity before the first of the month and the rise in activity after the first can explain the basic pattern of the results.

For some causes of death, the link between activity and mortality is obvious. One cannot die in a traffic accident unless one is in traffic and one cannot die from a murder unless one comes into contact with other people. To illustrate this point, in Table 6, we report the coefficients on days of the week dummy variables and some of the special day dummy variables for the cause-specific regressions originally reported in Table 4. There is amazing consistency in the results across the first three death categories. For traffic accidents, murders and other external causes, deaths spike on Saturdays and Sundays when more discretionary activity is involved. Likewise, across these three death categories, deaths spike on holidays associated with activity. Deaths from all three causes are higher on New Year's Eve and day, Holy Thursday and Good Friday, Memorial Day, July 4th, Labor Day, plus Christmas Eve and day. This distinct exception to this pattern is for suicides which peak on Mondays and fall considerably on most holidays except New Year's Day.

For other causes of death, extensive empirical evidence suggests that in an increase in activity temporarily raises mortality rates. No where is this more evidence than in the voluminous literature on the causes for the onset of heart attacks. Although there is extensive evidence that exercise and an active lifestyle reduce the overall chance of a heart attack and death by heart disease, nearly all activities seem to increase the chance of a heart attack at that particular moment. Mittleman et al. (1993) estimated that within an hour of strenuous physical exertion, the relative risk of a heart attack is almost 6 times higher than for people engaged in less strenuous or no activity. They also found that the risk declines for people who have engaged in more frequent exercise in the past. Albert et al. (2000) found in a study of over 21,000 patients without a history of heart disease that during and up to 30 minutes after physical exertion, the relative risk of sudden cardiac death rises by a factor of 17. Moller et al. (2001) found that among a sample of patients with a history of heart trouble, the relative risk of a heart attack one hour after sexual activity rose by a factor of 2.5 for physically active people and by a factor of 4.4 for those with a sedentary lifestyle. Lipovetsky et al. (2004) found a quadrupling of the relative risk of a heart attack in the first hour after a heavy meal. Phillips et al. (2004) found that both cardiac and non-cardiac diseases are about 5 percent higher than normal over the Christmas to New Years period compared to what one would expect for deaths during that time of year, a period of heavy travel and entertainment. In a meta-analysis, Witte et al. (2005) conclude that the incidence of sudden cardiac deaths are markedly higher on Mondays. The results are similar for both sexes and for those above and below age 65. Willich et al. (1994) conclude that the Monday effect for heart attacks only exists for workers. Franklin et al. (1996) and Heppell et al. document increased mortality after shoveling snow. Witte et al. (2000) found an increase in heart attacks in after the Dutch soccer team was eliminated by France in the 1996 World Cup while Berthier and Boulay (2003) found a decline in mortality among French men after the same event. Kirkup and Merrick (2003) found that mortality of males increased in the days after local soccer teams lost but they found no mortality effect for women. Carroll et al. (2003) found higher hospital admissions from a variety of causes the days after England lost to Argentina in the 1998 World Cup but there was no change in admissions after other games.

Given the structure of the MCOD data, we are unable to directly link increased activity to mortality. However, we can demonstrate that many consumer purchases and activities show the same within-month cycle as mortality. In the next two sections, we use a variety of data sets to document a within month consumption and purchasing cycle, which we use as a proxy for activity.

The results to follow are consistent with previous tests of the life cycle/permanent income (LC/PI) hypothesis (Hall, 1978). According to the LC/PI hypotheses, predictable changes in income should have no effect on consumption once the income is actually received. Numerous tests of the hypothesis using predictable changes in income demonstrate 'excess sensitivity'. Wilcox (1989) demonstrates changes in aggregate consumption when previously announced increases in Social Security payments went into effect. Similarly, Parker (1999) used data from the Consumer Expenditure Survey (CEX) to demonstrate that during the calendar year, consumption increased after individual taxpayer's incomes reached the maximum taxable amount. Using the same data, Souleles (1999) demonstrates an increase in consumption after the receipt of tax rebates. Not all results suggest there is excess sensitivity to predictable changes in income. Hsieh (2003) found no changes in consumption among Alaskan families when they received annual checks from the Alaska Permanent Fund, an annual check paid to residents in March that is funded by oil royalty to the state. In contrast, Hsieh found an increase in consumption following receipt of tax refund checks, amounts typically smaller than those distributed by the Alaskan Permanent Fund, suggesting that consumers are more likely to smooth consumption to large predictable changes in income.

Our work is most similar to that of Stephens (2003) who found an increase in consumption of time-sensitive purchases like perishable food and eating out at restaurants among seniors after the receipt of Social Security checks on the third of the month. Other papers have documented a similar drop in consumption before and then a hike in consumption after the receipt of scheduled income payments. Using data for the UK, Stephens (2006) found an increase in consumption after the receipt of pay checks.

Among Food Stamp recipients, Shapiro (2005) found a drop in daily caloric consumption of 10-15 percent over the food stamp month, a result he found was consistent with hyperbolic discounting. Likewise, among seniors, Mastrobuoni and Weinberg (2007) found a drop in food consumption over the month after the receipt of Social Security payments. However, the results were not uniform across all groups. Families with higher non-Social Security income smoothed consumption over the month while those with a higher fraction of income coming from Social Security showed pronounced decline in consumption as the distance from the receipt of benefits increased.

b. The Consumer Expenditure Survey

Following much of the previous work in this area, we initially examine the within-month consumption and purchase cycle using data from the Diary Survey component of the Consumer Expenditure Survey (CEX). The CEX is produced by the Bureau of Labor Statistics and it contains two major surveys. The first is the quarterly Interview Survey designed to capture purchases of more expensive and/or less frequently purchased items. The Diary Survey records purchases of less expensive and more frequently purchased items such as food, personal care items, and gasoline. The sampled unit for the Diary survey is a consumer unit which is a household containing related family members. Consumer units (CU) provide detailed information about purchases over two-consecutive 7-day periods and CU's begin their two-week survey cycle at various points in the month. At the end of the 14-day period, the survey collects detailed demographic data from each member of the CU.

The CEX data files are aggregated into quarterly files with all people who start their two week survey within the quarter in the file. We use data from people who began their two-week diaries from 1996 through 2004. We use data from three data sets. The first is the Consumer Unit Characteristics and Income file which is data about the household and household head. The second is the member characteristics income file which has individual observations for each CU member. The third is called the Detailed Expenditure File that that has as a unit of observation an individual purchase by a household member on a particular day. The data identifies the date and amount of the expenditure and records a Universal Classification Code (UCC) that categorizes all expenditures by detailed product type characteristics. We aggregate purchases of all family members to the daily level. Overall, we have data from 57,972 CUs and roughly 715,000 daily observations or about 12 daily observations per CU.

We generate three aggregate product categories. The first is all food purchases, both those for home and away from home. The second is called non-food items and includes goods and services that are purchased frequently. This group includes purchases on alcohol, cigarettes, apparel, gasoline, entertainment, personal products, personal services and over-the-counter drugs. The third is the sum of food and non-food items. We aggregate data into our synthetic month categories (December 18th through January 14th is month 1, etc) and divide all expenditures by the monthly Consumer Price Index (CPI) for all goods.[14]

In Table 7, we report regression estimates where we examine the determinants of daily household purchases for all the CUs in our sample. The outcome of interest is total daily spending for food, non-food and the combined. Dollar figures are in real 1982-1984 dollars. The key explanatory variables are three dummy variables, representing days -14 to -8, days 1-7 and days 8-14 within the synthetic month, with the week prior to the first of the month serving as the reference category. The other covariates include complete sets of dummies for the householder's age, sex, race, marital status and education. We also add descriptive information about the household including a complete set of controls for the region of the country, size of the urban area, family size and reported income.[15] We also add dummy variables for the day of the week, plus synthetic month and year effects and we allow for arbitrary correlation in errors within each CU.

The results in the three columns of Table 7 report results for food, other items and all items (food+other items), respectively. All three purchase categories show similar results with purchases prior to the first being lower than purchases after the first. Food purchases during the first week of the month are 13 cents higher than the preceding week, an amount that is 1.8 percent of the sample mean. Nonfood

---

[14] For synthetic month 1, we use the January CPI, for synthetic month 2 (January 18th through February 14th) we use the February CPI, etc.

[15] Income is reported in 9 groups. However, roughly 27 percent of the sample does not respond to the income question so we added a separate dummy for income not reported.

items shows a statistically significant increase of 7 cents a month but among all items, consumption is 23 cents higher in the forst week of the month compared to the previous week, an amount that is roughly 1.7 percent of the sample mean.

The magnitudes of these results are not large but they are very similar to the size of the peak to trough in the within-month mortality cycle. In section V, we will generate results by various population subgroups and demonstrate tremendous heterogeneity in the within-month consumption cycle.

c. Evidence from other consumer products and activities

In this section, we extend the results on a within-month consumption cycle past the CEX and consider data for some specific products and activities. The data for this section is aggregate time series data similar to the MCOD data earlier and the models are similar to those estimated for equation (1).

The first product we consider is the purchase of lottery tickets. Most states that run lotteries have one or several "daily number" games where contestants for $1, pick a three or four digit number and if their number is selected, they win $500 or $5000, respectively. We focus on these daily games to give us high frequency outcomes. We were able to obtain data on daily tickets purchased for pick 3 and pick 4 games in two states: Maryland and Ohio. Lottery ticket purchases are an interesting product line to consider because many credit cars issuers prohibit the purchase of tickets by credit cards. In some states, including Maryland, retailers are prohibited from accepting credits card payments for lottery ticket purchases.[16] Therefore, for most lottery transactions, consumers must use cash. If liquidity is an issue for consumers near the first of the month, then the within-month cycle for lottery tickets should be particularly large.

Maryland has a twice daily Pick 3 and Pick 4 game. Prior to May 23, 2004, there was no midday Pick 3 and 4 on Sundays. Starting on that date, the state went to twice daily games on Sunday. We obtained daily ticket sales for the Pick 3 and Pick 4 games in Maryland from January 1, 2003 through the

[16] http://www.mdlottery.com/resources/retailersreport.pdf

end of 2006. Ohio has a twice daily Pick 3 and Pick 4 game but there are no drawings on Sunday. We have data on tickets sales for these daily games from June 20, 2005 through June 16, 2007.

For both the Maryland and Ohio lotteries, we estimate models identical to those reported in Table 4 where the outcome of interest is the natural log of daily ticket sales, we control for artificial month and year effects plus day of the week effects, and dummies for the list of special days contained in footnote 7. Because the Maryland lottery added a second set of games on SundayMay 23 of 2004, we include a dummy for Sundays after that date. We also allow for arbitrary correlation in the errors for each artificial month times year cell.

The results from these two models are reported in the first two rows of Table 8. The data for lotteries shows a pronounced within-month purchase cycle with ticket purchases being about 8 percent higher in the first 7 days of the month compared to the previous week. Both of these results are statistically significant.

From a nationwide consulting firm for the retail trade sector,[17] we obtained data on average daily foot traffic through malls (from 1/1/2000 through 12/22/2007), all retail establishments (from 1/4/2004 through 12/22/2007) and apparel establishments (1/4/2004 through 12/22/2007). The data is collected from a large daily survey of retail establishments and malls.[18] The outcome of interest is the natural log of foot traffic through the establishments. The key difference between these models and ones estimated previously is that we delete Christmas day from the analysis since traffic on that day is substantially smaller than the rest of the year. The results for these models are reported in the middle of Table 8. For malls, all retail outlets and apparel stores, we estimate that foot traffic is 3.8, 5.7 and 5.8 percent higher during the first 7 days of the month compared to the previous week. These data show a pronounced within month activity cycle.

We obtained data on daily box office receipts for the top10 grossing movies within a one-week period (Friday through Thursday) from www.boxofficemojo.com for January 1, 1998 through June 7,

---

[17] As per our user agreement, we cannot identify the producers of the data.

[18] In a conversation with an executive at the company that produces these numbers, they indicated that their numbers are not adjusted to account for any end of the month effect.

2007. With this data, we use the natural log of the boy office receipts as the outcome of interest. The covariates in the model are identical to the ones used in the previous model with one exception. Because new movies are usually released on Fridays, and the top 10 movies can change dramatically from one week to the next, we define a week as a Friday to a Thursday period and add a dummy variable for each unique week in the data. The results for movies are reported in the sixth row of Table 8 and in this case, we see that the first week of the month generates 5.6 percent more in revenues than the previous week.[19]

We obtained data on daily attendance at major league baseball games from the 1973 -1998, 2000-2004 seasons[20] from http://www.retrosheet.org/schedule/index.html. The unit of observation is a game at a particular stadium and the dependent variable is log attendance. We control for standard covariates including dummies for opening and closing day, a dummy for whether it was after labor day or before memorial day, indicators for double headers, dummies for whether it was a day or night game interacted with the day of the week, plus dummies for the team pair in a year.[21] The results from this exercise show no within month cycle in baseball attendance.

We also had daily ridership on the DC Metro subway from January 1, 1997 through September 19, 2007. In these models, again the outcome of interest is log ridership and the extra controls are dummies for Redskin home games, days the Cherry Blossom festival is in effect and 5 dummies for exceptionally large crowds on the mall such as the Million Man march, etc. The results for this model which are presented in the last row of the table, show no within month mortality cycle.

V. Is Liquidity Responsible for these Within-Month Cycles?

---

[19] The difference between unadjusted (i.e., raw data) and regression adjusted results is largest for this outcome. The single biggest movie going week of the year is Christmas Eve through New Year's Eve. Over this period, average daily gross of the top 10 movies is more than twice what it is the rest of the year. Therefore, a plot of average daily gross by days in relation to the first of the month as in Figure 1 would show a tremendous spike in attendance before the first of the month. However, controlling for the special days throughout the year eliminates the Christmas effect on movies.

[20] There was no attendance data for the 1999 season on the web site.

[21] For example, there were separate dummies for each year of a Red Sox/Yankees game at Fenway.

In the previous two sections, we've demonstrated that in aggregate, the within-month mortality and consumption cycles show similar patterns. We've provided suggestive evidence that this may be due to liquidity in that the one good that must be purchased with cash, lottery tickets, shows the largest peak to trough. In this portion of the paper, we will examine in further detail whether liquidity problems at the end of the month that are resolved by the receipt of a paycheck or the payment of bills at the first are the cause for the decline.

The first of the month is a focal point of economic activities for many households. According to the 1996-2004 CEX samples used above, about 10 percent of respondents who report having a pay check are paid monthly and we suspect a large fraction of these people are paid on or near the first of the month. During much of the period of the analysis in this paper, most federal transfer programs distributed checks on or near the first of the month. As we note below and as outlined in Stephens, for Social Security recipients who claimed benefits prior to April of 1997, received checks on the third of each month. Supplemental Security Income payments have always been paid on the first of the month. In our survey of state Temporary Assistance for Needy Family programs, the vast majority of states distribute checks during the first week of the month.

Likewise, many families have periodic bills that are due on one near the first of the month. In our CEX samples, fully 50 percent of all households who paid a mortgage or rent payment sometime in their 14-day survey period did so on the day before the 1st of the month or during the first week of the month, with 14 percent of the sample paying on the 1st of the month. Since most rent and mortgage payments must be paid by check or cash, uncertainty about whether there will be enough in the bank at the start of the month may force some to ratchet down spending until after the bills are paid at the start month.

In this section, we provide some suggestive evidence that liquidity issues play a role in the within-month consumption and mortality cycles. Specifically, we demonstrate that those groups we would expect to have greater liquidity issues at the turn of the month are precisely those groups with the greatest peak to trough in the within-month consumption and mortality cycles.

a. Heterogeneity in the Within-Month Consumption Cycle

The within-month purchase cycle that we document with the CEX in Table 7 varies tremendously based on observed characteristics of the reference person and the CU. In each case, we find evidence that the within-month consumption cycle is greatest for those we would expect to be more likely to face liquidity issues at the end of the month. In Table 9, we report three sets of estimates from the CEX data where the samples are split into three groups based on characteristics of the household or the household's reference person: In the first row of results, we break the samples based on the education level of the reference person within the CUs. The three groups are for reference people with less than a high school education, a high school education and/or some college, and those with a college degree or more.

Among those households with a lower educated reference person, food expenditures drop considerably before the first of the month but non-food items do not show as dramatic of a within-month cycle. The coefficient on days 1-7 for food items is a statistically significant 47 cents which is 8 percent of the sample mean. Among CUs with high school educated reference person, the CEX data demonstrates statistically significant within-month purchase cycles for all three expenditure categories. In the all items category, the coefficient on the days 1-7 dummy is about 4 percent of the sample mean of $12.48 in daily spending. Finally, in CUs with the most educated reference member, we find no evidence of a within month consumption cycle for food, some evidence of a cycle for non food items although the estimates are statistically insignificant. In the highest education group, in the all items models, we estimate a statistically insignificant coefficient of 13.5 cents in Week 1 which is less than 1 percent of the sample mean in daily purchases.

In the next group of results, we generate estimates for three mutually exclusive groups based on their receipt of income from the federal government. In the first block of estimates, we restrict the sample to those households that have any federal or state income assistance other than Social Security. The bulk of these families will be receiving income on either Temporary Assistance for Needy families (TANF) or Supplemental Security Income (SSI) program. SSI payments are on the first of the month and our email survey of 39 state TANF offices indicates that most states pay TANF payments in the first week of the year. In this subsample, there is a substantial within month purchasing cycle. We find that for food, consumption is $1.36 higher during the first week of the month compared to the previous week, an amount that is 21 percent of the sample mean. We find that non-food consumption is higher in the first week as week but this result is not statistically significant. For all items, we estimate a statistically significant increase in purchases of $1.79 in the first week of the month compared to the previous week, an amount that is 16 percent of the sample mean.

In the next block of results, we restrict the sample to those households with Social Security income but no other income from federal programs such as SSI or TANF. This is similar to the sample used in Stephens (2003). Stephens exploits the fact that Social Security checks are distributed on the third of the month to examine whether there is excess sensitivity in purchases. If the LC/PI hypotheses are correct, the expected receipt of Social Security checks should not alter spending so the demonstration of a within-month purchase cycle would falsify the predictions of these models. Stephens used data the 1986-1996 period. Our sample is more recent than that used in Stephens. More importantly, the timing of Social Security payments has changed in the past decade. For those who claimed Social Security prior to May 1997, payments are still made on the third of the month. For those claiming May 1997 and after, payments are made on the first, second or third Wednesday of the month, depending on whether the birth date is on the 1st through 10th, 11th through 19th or 20th through 31st, respectively.[22] Therefore, our sample is a mix of people being paid under both systems.

As the results in Table 9 indicate, for households with any Social Security income, food purchases, non-food purchases and all items have statistically significantly higher purchases on days 1-7 of the month than in the week prior to the first. The coefficients for days 1-7 in these three categories are 0.348, 0.254 and 0.585, respectively, which represent about 5.6 percent of mean daily consumption in each category.

In the final column of results, we restrict attention to a sample of households that has neither Social Security income nor income from other federal or state transfer programs. This set of estimates provides no evidence of a within-month mortality cycle.

---

[22] http://www.socialsecurity.gov/pubs/calendar.htm.

In the next group of results, we construct subsamples based on the income of the households. We use three groups in total, those with incomes less than \$30,000, households with incomes of \$30,000 and more, and households that do not report income. Since the average education of the reference person in households not reporting income is closer to the education of the reference person in the lower income group, it is no surprise that these two groups of results are similar. Among low income households, we find a statistically significant coefficient on the Days 1-7 dummy for all three spending categories. In the all items model, the coefficient of 40 cents is about 4 percent of the sample mean. Among higher income families, we actually find a negative and statistically significant coefficient on the days 1-7 dummy variable monthly. For this higher income group, there is little if any within-month consumption cycle for non-food items and all items categories.

The results from the CEX provide clear evidence of a within-month consumption cycle that is consistent with the mortality results presented above. The evidence also points towards liquidity driving the purchase cycle in that low income and lower educated groups demonstrate a within-month purchase cycle yet higher income and more educated households exhibit no such tendencies. Finally, the cycle appears to be tied heavily to payments from federal transfer programs in that the cycle is only present for households with ties to these programs. The results may also be consistent with a hyperbolic discounting as suggested by Shapiro (2005) and Mastrobuoni and Weinberg (2007).

b. Mortality Results by Education Levels

While the Multiple Cause of Death data have no direct measure of income and wealth, decedent's highest level of educational attainment has been recorded since 1989. Educational attainment is strongly and positively correlated with households' wealth and financial savings (Juster, Smith and Stafford, 1999). The Consumer Expenditure Survey, a dataset in which education, income and purchase activity is recorded, shows both low levels of income and low educational attainment are associated with the largest peak-to-trough in spending over the course of the month. In this section we see if similar patterns are observed for the relationship between educational attainment and within-month mortality cycle.

As discussed in the overview of the mortality data, education information is generally provided by the next of kin and is accurate approximately 70 percent of the time, with educational attainment being overstated on average (Sorlie and Johnson, 1996). We group decedents are group into three categories: those whose highest education is less than high school completion, those whose highest education is high school completion, and those who completed college or higher.[23]

The relative mortality risks for these three groups are shown in Figure 6. Panel A shows the within-month mortality cycle for decedents with less than high school education. The average fatality counts for all fourteen days leading up to the first of the month are below the daily average, and are 0.9 percent and 0.6 percent below average on the two days prior to the first. On the first of the month, counts increase to 0.5 percent above the average before peaking at 0.8 percent above the average prior on the fifth. The within-month mortality pattern for high school completers (in Panel B) is broadly similar, with a reduction in mortality prior to the first of the month on the order of 0.5 percent increasing to 1 percent above the average on the first of the month. The 95 percent confidence intervals in Panels A and B show these differences are statistically different from average daily mortality, except for the confidence interval around high school completer's *Day 2* relative mortality risk.

The daily relative mortality risk for the college-educated is shown in Panel C of Figure 6.[24] There is not the same within-month cycle evident in the other two groups. Point estimates no longer consistently lie below the average prior to the first of the month (seven of fourteen do) and above the average after the first (eight of fourteen do). There is an increase from *Day -1* to *Day 1*, but it is not large and both confidence intervals include the average daily mortality risk.

---

[23] Between 1989 and 2002, the number of years of schooling rather than education outcomes are recorded in the MCOD file. Decedents were classed as having less than a high school education is they reported three or fewer years of high school; having a high school education if they completed four years of high school but fewer than four years of college; and having completed college if they had four or more years of college education.

[24] An adjustment is made here for the September 11 terrorist attacks as there are nearly four times as many college-educated decedents (2,643) as on the previous day (682) and the change that is large enough to distort this analysis. We remove this difference from the *Day 11* aggregate count. This event does not affect the other two education groups to the same degree so they are not adjusted (high school completers have 26% higher mortality on September 11, 2001 compared to the previous day, while non-completers fatality counts appear largely unaffected).

The results from regressions with week-of-month dummies for these three education-based groups are show in Table 10. *Week 2* is again the reference week. Once special days and other controls are introduced in a regression framework, a within-month cycle is present for all three education groups. The largest change from *Week -1* to *Week 1* is for those who did not complete high school (1.0 percent), followed by high school completers (0.93 percent) and those with a college education (0.45 percent). The *Week 2* coefficients display the same pattern, with it higher for high school non-completers (0.93 percent) than high school completers (0.72 percent) and college-educated decedents (0.23 percent). Apart from the Week 2 coefficient for in the college-educated regression, all of these coefficients are statistically significant at conventional levels; none of the *Week -2* coefficients are statistically different from Week 1. The differences in the mortality patterns by different levels of education attained are consistent with variations in liquidity over the month affecting the relative mortality risks different groups face.

c. Social Security Payments and the Elderly

As we noted above, Stephens (2003) documented that Social Security recipients do not smooth their consumption over the month, but instead spend more in the first few days after the receipt of their checks compared to the days prior to its arrival. Our results from Table 9 replicate the basic results from Stephens with similar but slightly different product categories. Since payment receipt has been shown to increase activity as proxied by consumer expenditures, if mortality and activity are related then mortality should follow the same pattern. In this section, we exploit the timing of Social Security payments and the pervasiveness of seniors' reliance on them to draw a link between liquidity and mortality.

Before looking at the role of Social Security payments, it is worth looking at what the mortality cycle looks like for seniors. Recall from Table 2 that for the elderly we found a statistically significant increase in mortality during the first week of the month. However, this peak to trough was the lowest for any age group. The existence of a mortality cycle amongst seniors makes it meaningful to consider the timing of their income payments, and indeed as a group they likely contribute more to the aggregate patterns than non-seniors.

Prior to May 1997, all Social Security beneficiaries received their checks on the 3rd of each month or, when the 3rd fell on a weekend, the Friday prior to the 3rd.[25] This creates a schedule of Social Security payments that varies slightly with respect to the days of the calendar month, which can be used to see if mortality varies in line with the timing of payments.

As checks not paid on the 3rd are always paid on Fridays, day-of-the-week effects may obscure any pattern in raw counts. Therefore, to isolate the impact of when checks are received from other factors, we estimate a model similar to that specified by equation (1). However, we eliminate the dummy variables that identify days in relation to the start of the month and instead, replace them with a series of dummies that identify days in relation to their proximity to the Social Security payment day. For example, when payment is on the third of the month, the 1st of the month is assigned *Payday -2*, the 2nd is *Payday -1*, the 3rd is *Payday 1*, and so on. When payment occurred on the 2nd of the month, all of the Payday variables shift one day earlier. The *Payday* coefficients therefore show the pattern in relation the day of Social Security payment, controlling for month and year effects, the special days plus day of the week effects. The reference day is the day before the payment date (*Payday -1*).

The OLS results for a sample of deaths aged 65 and older between 1973 and 1996 are shown in Table 11, and provides suggestive evidence that seniors' mortality is influenced by the arrival of Social Security payments. Mortality is 0.6 percent higher on the day that Social Security is paid compared to the previous day, before peaking the following day at 0.8 percent above the Payday -1 reference day. For all fourteen days after payment, mortality remains positive and statistically different from the day prior to Social Security payments arriving. A "first of the month" effect still seems to remain as evidenced by a reduction in mortality of 0.55 percent percent three days prior to Social Security payments, which is most commonly the last day of the previous month. With mortgage, rent and credit card payments often occurring at the beginning of the month, this "residual" calendar pattern may also be due to liquidity patterns.

[25] When the 3rd of the month is Labor Day, checks are distributed on August 30th.

We can also use more direct variation in the timing of Social Security payments to see whether the changes in liquidity they generate affect mortality. Starting in May of 1997, the timing of monthly payments for new recipients depended on their birth dates. Those with a birth date on the 1^{st} to the 10^{th} were paid on the second Wednesday of each month, those with a birth date on the 11^{th} to the 20^{th} were paid on the third Wednesday of each month and those with a birth date on the 21^{st} to the 31^{st} were paid on the fourth Wednesday of the month. Those already receiving payments on the 3^{rd} of a month continued to receive checks as they had before.[26]

We have information on decedents' date of birth in the restricted-use MCOD held by the National Center for Health Statics, so we are able to assign Payday dummies based on this new payments schedule in the same way as we did for the traditional, "3^{rd} of the month" schedule. We do not have information on who is on social security or when decedents retired. Given that people commonly claim social security between 62 and 65 years of age, this means that over the 1997 through 2000 time period there are few decedents aged 65-69 that we can be sure were receiving Social Security payments under the new schedule when they died. Therefore, we restrict our analysis to those aged 65 to 69 years who died between 2001 and 2005. The majority of decedents in this sample should be receiving payments under the new schedule although there should be some 67-69 year olds in 2001, 68-69 year olds in 2002 and 69 year olds in 2003 who could be receiving payments under the old schedule.

To explore the effect of this change in Social Security payment schedules, we consider three regression-adjusted patterns. First, to provide a better comparison than the results in Table 9, we regressed the natural log of fatality counts for 65 to 69 year olds between 1992 and 1996 on *Payday* dummies based on the traditional "third of the month" schedule and other controls. The reference day is still the day prior to Social Security being paid. The results for this regression are in left panel of Table 12, and show the same relationship between payment and mortality as in Table 9. Compared to *Payday -1*, mortality is 1.6 percent higher the day Social Security is paid and 2.3 percent higher two days after

[26] http://www.ssa.gov/pubs/2007calendar.htm.

Social Security is paid. Despite the smaller sample, these differences are statistically significant at conventional levels.

Second, this same regression based on the traditional “third of the month” payment cycle is done on the natural log of fatality counts for 65 to 69 year olds who died between 2001 and 2005. Since most decedents in this group are unlikely to be on the old schedule, the patterns observed for this group between 1992 and 1996 should largely disappear. The results of this regression are shown in the middle panel of Table 10, and this is what happens. Relative to *Payday -1*, none of the coefficients in the first week after Social Security has traditionally been paid is statistically different from zero and many are negative.

To see if a relationship between mortality and the new payments schedule for this group can be found, the third regression-adjusted pattern is based on dummies related to this new schedule. Decedents were allocated dummies based on date of birth. For example, those born between the 1^{st} and the 10^{th} of the month were assigned *Payday 1* on the second Wednesday of the month, *Payday 2* on the second Thursday of the month, and so on. In the same way, those born between the 11^{th} and 20^{th} were assigned *Payday* dummies with *Payday 1* on the third Wednesday of the month, and those born between the 21^{st} and the 31^{st} were assigned *Payday* dummies with *Payday 1* on the fourth Wednesday of the month. Dummies range between *Payday -8* and *Payday 14*, because payments always occurring on Wednesdays mean additional dummies would be collinear with day-of –the-week controls. As before the reference day is *Payday -1,* days outside the 28 days around the payment are dropped, and controls are introduced for special days, weekday, and month and year effects. The payment schedule is now significantly different from the synthetic months centered around the first of the month that new synthetic months and years based around *Payday 1* are constructed for the three groups. For the regression, the three groups' fatality counts and covariates are then placed in one data file for analysis.

The results of the regression are shown in the right panel of Table 12. There is no clear pattern based on the new schedule. In fact, this new set of variables performs relatively poorly in terms of accounting for the variation in these fatality counts. Difficulty in determining who enrolled in Social

Security after May 1997 creates measurement error; there is also measurement error in that decedents in this group could be getting paid on their spouses' date of birth rather than their own.

Overall, there is suggestive evidence that seniors' mortality is connected to when they receive income. Prior to 1996, mortality patterns of the types found throughout the paper emerge in relation to the traditional social security payment schedule. These patterns are no longer present for 65 to 69 year olds who died between 2001 and 2005, people who are unlikely to be on this old schedule. In unreported results, we regress fatality counts of those aged 70 to 75 who died between 2001 to 2005 on measures of the traditional Social Security payment schedule to check that there is not something about the post-2000 period that generally made any payment-mortality linkage disappear. The majority of these people should be on the traditional schedule, and we do observe a positive and statistically-significant increase in mortality on the first few days after Social Security is paid. This makes the absence of a pattern during this period amongst 65 to 69 year olds more likely to be due changes in Social Security.

VII. Understanding Mortality over the Business Cycle

This examination of the broader relationship between liquidity, activity and mortality has implications for research on mortality over the business cycle. A voluminous literature with contributions from a variety of disciplines has established that health outcomes are much better among individuals with higher socioeconomic status. A relationship between health and socioeconomic status has been documented for virtually all measures of health and health habits including mortality (Backland, Sorlie and Johnson, 1996), self-reported health status (House, Kessler, and Herzog, 1990), measures of child health (Case, Lubotsky and Paxson, 2002), smoking (Chaloupka and Werner, 2000), obesity (Chang and Lauderdale, 2005), the incidence of disease (Banks et al., 2006), a variety of cardiovascular risk factors (Karlamangla et al. 2005) and a variety of biomarkers (Steptoe et al., 2002a and 2002b; Goodman et al. 2005; Ridker et al. 2000; Muenning, Sohler and Mahato, 2007).

In contrast to this work is a more recent strand of literature documents that mortality is pro-cyclic. The basic statistical relationship has been documented for the United States (Ruhm, 2000) and a variety of OECD countries (Gerdtham and Ruhm, 2005; Neumayer, 2004; Tapia Granados, 2004), for a number of health habits (Ruhm, 2003) and health outcomes (Ruhm, 2005) and for a wide variety of causes of death including heart disease, certain cancers, murder (Ruhm, 2000), motor vehicle fatalities (Evans and Graham, 1988) and infant health (Dehejia and Lleras-Muney, 2004).

The methodology for documenting the pro-cyclic nature of mortality dates to Evans and Graham (1988) and is typified in Ruhm (2000). Using pooled time-series/cross-sectional data at the state level, authors regress mortality rates on state and year effects, some measure of the business cycle, plus other demographic covariates. The measure of the business cycle is typically the unemployment rate and for the vast majority of death categories, the coefficient on the unemployment rate is negative indicating that mortality is pro-cyclic. The one death category that shows a decided counter-cyclic pattern is however suicides (Ruhm, 2000).

The disparity between the older literature on socioeconomic status and health and the more recent work on mortality and the business cycle is not all that surprising. Typical measures of socioeconomic status include variables such as education, wealth, income or occupational status can all be considered measures of permanent income. In contrast, the econometric models used to test the cyclicality of mortality all use within-group estimators that hold state characteristics constant and ask whether year to year fluctuations in the unemployment rate alter mortality. These later models are therefore measuring the impact of transitory changes in economic activities on mortality.

What has been missing from this more recent literature, however, is an explanation for the procyclicality of mortality. Ruhm (2005a and 2005b) provides some evidence that smoking, severe obesity, very heavy drinking, and a sedentary lifestyle decline during economic downturns but to date, no decomposition has idetified whether these habits explain the changes in mortality. Ruhm (2005b, p. 1210) concludes that "…research needs to better indentify mechanisms for the procyclic variation in mortality."

The results above linking activity to mortality do however suggest a possible explanation for the pro-cyclic nature of mortality. As the economy expands, people naturally engage in more economic activity. They drive more, go out to dinner more often, go to the movies. Because the temporal variations in activity has an impact on mortality, it is therefore no surprise that hikes in mortality should follow. If this hypothesis is true, then we should see a similarity in the size of the within month mortality cycle and the correlation with the business cycle across specific causes of death.

The size of the within-month mortality cycle for specific causes of death is presented in Table 4 above where we disaggregate the data into 15 mutually exclusive causes of death. We use the same data aggregated to a different level to generate estimates of the impact of the business cycle on mortality. Specifically, we first use data for the 1976-2004 period to construct annual mortality rates for each state. Let M_{it} be the mortality rate for state i in year t, defined as deaths per 100,000. Following Evans and Graham (1988) and Ruhm (2000), the within-group model we estimate is of the form:

$$(2) \quad \ln(M_{it}) = X_{it}\beta + UNEMP_{it}\alpha + u_i + v_t + \varepsilon_{it}$$

Where X_{it} is a vector of demographic characteristics, u and v are state and year effects and ε is an idiosyncratic error. The key covariate is the state i's unemployment rate in year t ($UNEMP_{it}$). In the model, we include in x the fraction of people that are under 18, the fraction of residents 65 and over, and the fraction black. In the model, we allow for arbitrary correlation in the errors within a state.

Results from this regression are reported in Table 13. In the first row, we report estimates for all-cause mortality and these results show a large, negative and statistically significant impact of the unemployment rate on mortality. A one percentage point drop in the unemployment rate will increase mortality by about .4 percent which is about 20 percent lower than the estimate in Ruhm (2002, Table II, column a).

In the next 15 rows, we generate estimates of the pro-cyclicality of mortality for specific causes. The results for this are consistent with previous estimates in that traffic accidents, murders, other external causes, heart attacks, COPD and other causes demonstrate a statistically significant procyclic relationship, at least at a p-value of 0.1. The data suggests some notable statistically significant counter-cyclic outcomes in suicides, lung cancers, other cancers and while diseases like cancers, leukemia, heart disease, and non-alcohol cirrhosis have a weak statistical relationship with the business cycle. The pattern of results is quite similar to that in Table 4. To demonstrate this point, in Figure 8, we plot the coefficients on the unemployment rate from Table 13 along the x axis and the within-month peak to trough estimates (the coefficient on the Days 1-7 dummy variable) from Table 4. The graph shows a pronounced negative relationship and the correlation coefficient between the two series is -0.4. There is one obvious outlier: suicides. Suicides are decidedly counter cyclic yet it has a very large within month mortality cycle. Excluding this cause of death however, the correlation between the remaining 14 points is -0.8 and an OLS line through these 14 points (excluding suicides) shows a strong negatve relationship between the two sets of values . Overall, if the within month mortality cycle is indeed driven by a rise in activity, then the similarity in the results across death categories between this cycle and the pro-cyclicality of mortality suggests provides suggestive evidence that activity is the underlying cause for both.

VIII. Conclusion

Previous work on the within-month mortality cycle has not been able to rule out drug and alcohol consumption having a role in deaths not obviously caused by substance abuse. Here, a comprehensive attempt to identify deaths where substance abuse may have had a role and an investigation of the temporal patterns specific causes of death show it is implausible that substance abuse is the sole reason deaths drop off in the days prior to the first of the month and then spike to above-average levels on the first.

We find that many activities, such as consumer purchases, mall visits and cinema attendance, exhibit a similar within-monthly cycle. While we do not have activity and mortality information in a single dataset, existing medical knowledge of the triggers for specific health conditions and the similarity and the patterns suggest short-term changes in activity may be the missing explanation for the within-month mortality cycle. This is made more likely by the patterns in activity and mortality being consistent with many people experiencing liquidity variations over the month, which change their levels of activity and in turn affect the number of deaths that occur on particular days.

These results link medical literature on the within-month mortality cycle and the economics literature on consumption smoothing, with implications for both. First, for the medical literature, understanding substance abuse as only part of the within-month mortality cycle means liquidity and payments have broader medical effects than is commonly thought, and that “full wallets” do not just mean increases in drug-related attendances in emergency departments but likely have an effect of many more aspects of health and health services provision. Second, in terms of consumption smoothing, this result points to the potential breadth of excess sensitivity of consumption to the timing of payments. There are over 70 million records in the mortality data we use, and we estimate approximately 15 percent of the within-month cycle may be accounted for by substance abuse. If the remaining part of the pattern is due to liquidity changes affecting activity, then all of our demographic groups having a within-month cycle suggests that excess sensitivity and its explanations (such as hyperbolic discounting) must not be limited to narrow subpopulations.

The results also have implications for our understanding of the procyclicality of mortality. The causes of death and demographic groups with the largest within-month mortality cycle also exhibit the most procyclical mortality, suggesting that whatever drives the within-month mortality cycle also causes mortality to be procyclical. Short-term changes in liquidity can be more easily separated from permanent levels of income over a month rather than over a business cycle, and this explanation for the within-month mortality cycle and the similarity of the two mortality phenomena suggests the apparent contradiction between the protective effect of income and the procyclicality of mortality can be resolved by looking at business cycle movements as temporary, medium-term changes in liquidity that change activity levels and mortality risks people face.

Several questions remain unanswered. The most important one is whether these short-term variations in liquidity and activity are changing the total number of deaths or changing the timing of deaths of susceptible people by several days (what epidemiologists refer to as “harvesting”). For some causes, such as motor vehicle accidents, it is logical that activity leads to an increase in deaths, but for other conditions the answer is not clear.

Another question is why there is a difference between the pattern of suicides within months and over business cycle. There are also questions as to how the “liquidity, activity, mortality” relationships interact with the weather, which may affect both levels of activity and how activity affects health outcomes in ways that means the outcomes are ambiguous.

References

Albert CM, Mittleman MA, Chae CU, Lee IM, Hennekens CH, Manson JE, 2000. "Triggers of Sudden Death from Cardiac Causes by Vigorous Exertion," *New England Journal of Medicine,* 343, 1355-1361.

Berthier F, Boulay F. Lower Myocardial Infarction Mortality in French men the day France won the 1998 World Cup, 2003. *Heart* 89(5), 555-6.

Carroll D, Ebrahim S, Tilling K, Macleod J, Smith GD, 2003. Admissions for Myocardial nfarction and World up Football: Database Survey. *British Medical Journal* 325(7378): 1439-42.

Collins DJ, and HM Lapsley, 2002, "Counting the cost: estimates of the social costs of drug abuse in Australia in 1998-9," National Drug Strategy Monograph Series No. 49, Commonwealth Department of Health and Ageing, Canberra. Available at: http://www.health.gov.au/internet/main/publishing.nsf/Content/phd-monographs-49-cnt [Last accessed: September 24, 2008].

Cook P, Tauchen G, 1982. "The Effect of Liquor Taxes on Heavy Drinking," *Bell Journal of Economics,* 13, 379-389.

Dehejia R, Lleras-Muney A, 2004. Booms, Busts, and Babies' Health. *Quarterly Journal of Economics* 119(3), 1091-1130.

Dobkin C, Puller SL, 2007. "The Effects of Givernment Transfers on Monthly Cycles in Drug Abuse, Hospitalization and Mortality," *Journal of Public Economics,* 91(), 2137-57.

Elliott WJ, 2001. "Cyclic and Circadian Variations in Cardio Vascular Events," *American Journal of Hypertension,* 14(9), S291-95.

Evans WN, Graham JD, 1988. Traffic Safety and the Business Cycle. *Alcohol, Drugs and Driving* IV, 31-38.

Foley, CF, 2008. Welfare Payments and Crime, NBER Working Paper No. 14074, June 2008.

Franklin, BA, Bonzheim K, Gordon S, Timmins GC, 1996. "Snow Shoveling: A trigger for acute myocardial infarction and sudden coronary death," American Journal of Cardiology, 77(10), 855-8.

Gerdtham UG, Johannesson M, 2005. Business Cycle and Mortality: Results from Swedish Microdata. *Social Science and Medicine* 60, 205-218.

Hall, RE, 1978. "Stochastic Implications of the Life Cycle-Permanent Income Hypothesis: Theory and Evidence," *Journal of Political Economy* 86(6), 971-87.

Halpern S, Mechem CC, 2001. "Declining rate of Substance Abuse Throughout the Month," *The American Journal of Medicine,* 110(5), 347-51.

Harwood H, Fountain D, and G Livermore, 1998, The Economic Costs of Alcohol and Drug Abuse in the United States 1992, Appendix A: Health Disorder Codes, National Institutes on Drug Abuse. Rockville, MD Available at: http://www.drugabuse.gov/EconomicCosts/Index.html [Last accessed: Sept 24, 2008].

Heppell R, Hawley SK, Channer KS. 1991. "Snow shoveller's infarction." *British Medical Journal,* 302, 469-470

Juster FT, Smith JP, Stafford F. 1999. The Measurement and Structure of Household Wealth. *Labour Economics*, 6, 253-275.

Kirkup W, Merrick DW, 2003. A Matter if Life and Death: Population Mortality and Football Results. *Journal of Epidemiology and Community Health*, 57(6), 429-32.

Li X, Sun H, Marsh DC, Anis AH, 2007. “Impact of Welfare Cheque Issue Days on a Service for those Intoxicated in Public,” *Harm Reduction Journal*, 12(4)

Maynard C, Cox GB, 2000. “Association Between Week of the Month and Hospitalizations for Substance Abuse,” *Psychiatric Services* 51(1), 31.

Mastrobuoni G, Weinberg M, 2007. “Heterogeneity in Intra-Monthly Consumption Patterns, Self-Control, and Savings at Retirement.” Working Paper No. 25. Collegio Carlo Alberto.

Mittlemen MA, Maclure M, Tofler GH, Sherwood JB, Goldberg RJ, Muller JE, 1993. Triggering of acute myocardial infarction by heavy physical exertion. Protection against triggering by regular exertion. Determinants of Myocardial Infarction Onset Study Investigators.*New England Journal of Medicine,* 329(23), 1677-83.

Moller J, Ahlbom A, Hulting J, Diderichsen F, de Faire U, Reuterwall C, Hallqvist, 2001. Sexual Activity as a Trigger of Myocardial infarction: A Case Crossover Analysis in the Stockholm Heart Epidemiology Programme (SHEEP), *Heart* 86(4), 387-90.

Neumayer E, 2004. Recessions Lower (Some) Mortality Rates: Evidence from Germany. *Social Science and Medicine* 58, 1037-47.

Parker JA, 1999. “The Reaction of Household Consumption to Predictable Changes in Social Security Taxes,” *American Economic Review,* 89(4), 959-73.

Phillips, DP, Jarvinen BA, Abramson BA, Phillips RR, 2004. “Cardiac Mortality in Higher Around Christmas and New Year’s Than at Any Other Time,” *Circulation*, 110(25), 3781-88.

Riddell C, Riddell R, 2006**. “**Welfare Checks, Drug Consumption, and Health: Evidence from Vancouver Injection Drug Users**.”** *Journal Human Resources*, 41(1)**,** 138-161.

Riley ED, Moss AR, Clark RA, Monk SL, Bangsberg DR, 2005. “Cash Benefits are Associated with Lower Risk Behavior among Homeless and Marginally Housed in San Francisco,” *Journal of Urban Health* 82(1), 142-150.

Rosenheck RA, Dausey DJ, Frisman L, Kasprow W, 2000. “Outcomes After initial Receipt of Social Security benefits Among Homeless Veterans with Mental Illness,” *Psychiatric Services* 51(12), 1549-54.

Ruhm, CJ. 2000. Are Recessions Good for your Health? *Quarterly Journal of Economics,* 115(2), 617-650.

Ruhm, CJ. 2003. God Times Make You Sick. *Journal of Health Economics* 22, 637-658.

Ruhm, CJ. 2005. Healthy Living in Hard Times. *Journal of Health Economics,* 24(2), 341-363.

Ruhm, CJ. 2005b. Commentary: Mortality Increases During Economic Upturns. *International Journal of Epidemiology* 34(6), 1206-1211

Single E, Robson L, Rehm J, Xie X, 1999, Morbidity and mortality attributable to substance abuse in Canada. *American Journal of Public Health*, 89: 385-90.

Shapiro JM, 2005. "Is There a Daily Discount Rate? Evidence from the Food Stamp Nutrition Cycle." *Journal of Public Economics*, 89(2), 303-325.

Sorlie, PD, Johnson NJ, 1996. "Validity of education Information on the Death Certificate." *Epidemiology*, 7(4), 437-39.

Souleles NA, 1999. "The Response of Household Consumption to Income Tax Refunds." *American Economic Review* 89(4), 947-58.

Stephens Jr, M, 2003. "'3rd of the Month'; Do Social Security Recipients Smooth Consumption Between Checks," *American Economic Review* 93(1), 406-22.

Stephens Jr, M, 2006. "Paycheque Receipt and the Timing of Consumption," *The Economics Journal* 116(513), 680-701.

Swartz JA, Hsieh C, Baumohl J, 2003. "Disability Payments, Drug Use and Representative payees: An Analysis of the Relationships," *Addiction* 98(7), 965-975.

Tapia Granados JA, 2005. Increasing Mortality During the Expansions of the US Economy, 1900-1996. *International Journal of Epidemiology* 34, 1194-1202.

Toubiana L, Hanslik T, Letrilliart L, 2001. French Cardiovascular Mortality did not Increase During 1996 European Football Championship. *British Medical Journal*, 322(7297), 1306.

Verhuel G, Singer SM, Christenson JM, 1997. "Mortality and Morbidity Associated with the Distribution of Monthly Welfare Payments," *Academy of Emergency Medicine*, 4(2), 91-2,

Wilcox D, 1989. "Social Security Benefits, Consumption Expenditures, and the Life Cycle Hypothesis." *Journal of Political Economy* 97(*), 288-304.

Willich SN, Lowel H, Lewis M, Hormann A, Arntz HR, Keil U, 2000. "Weekly Variation of Acute Myocardial Infarction. Increased Monday Risk in the Working Population." *Circulation*, 90(1), 87-93.

Witte DR, Bots ML, Hoes AW, Grobbee DE, 2000. Cardiovascular Mortality in Dutch Men During 1996 European Football Championship: Longitudinal Population Study. *British Medical Journal*, 321(7276), 1553-4.

Witte DR, Grobbe DE, Bots ML, Hoes AW, 2005. A Meta Analysis of Excess Mortality on Monday. European Journal of Epidemiology, 20(5), 401-6.

Figure 1: Relative Daily Mortality Risk (95% Confidence Intervals) by Day in Relation to the First of the Month, 1973-2005 MCOD, All Deaths, All Ages

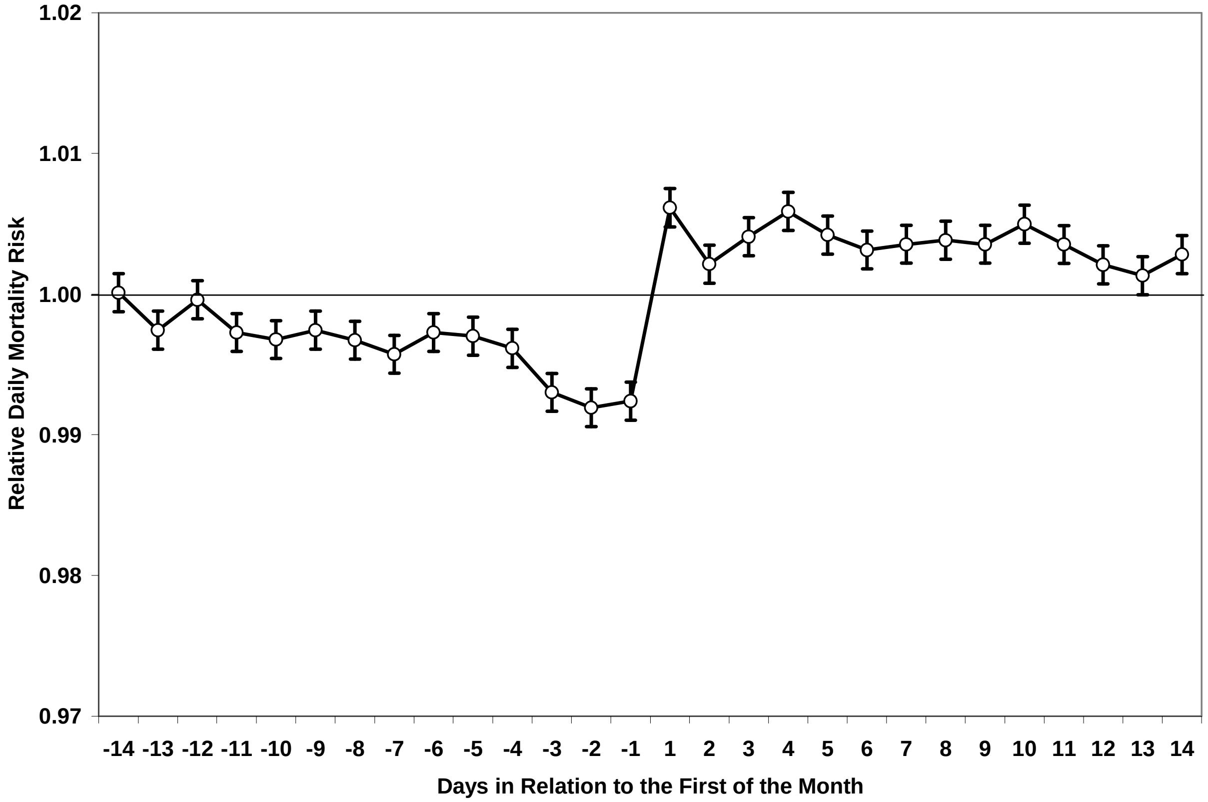
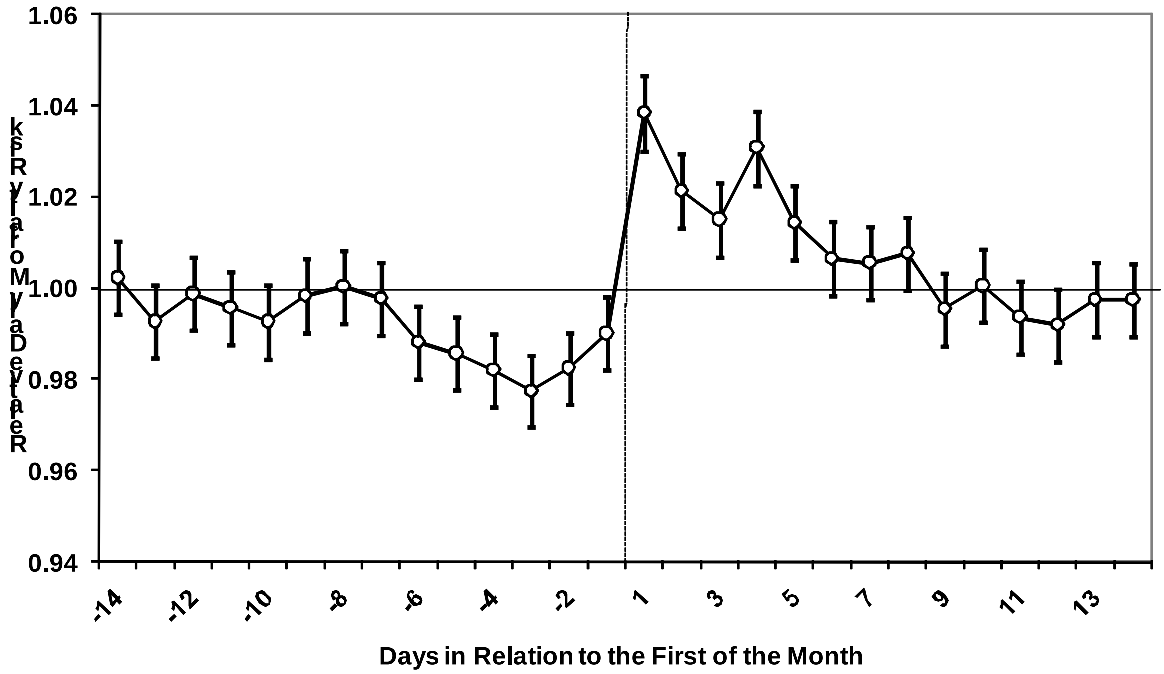


Figure 2: Relative Daily Mortality Rates (95% Confidence Intervals), With and Without Mention of Substance Abuse, 1978-1998 MCOD, All Ages

A: Substance Abuse Related



B: Non-Substance Abuse Related

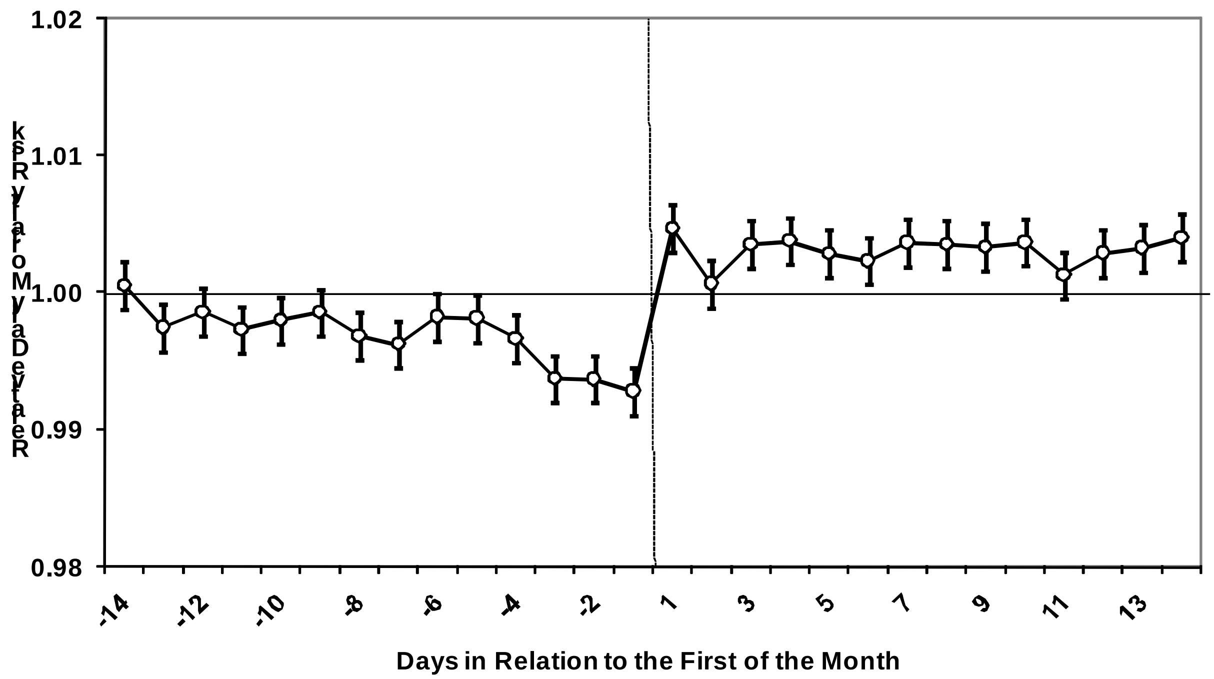
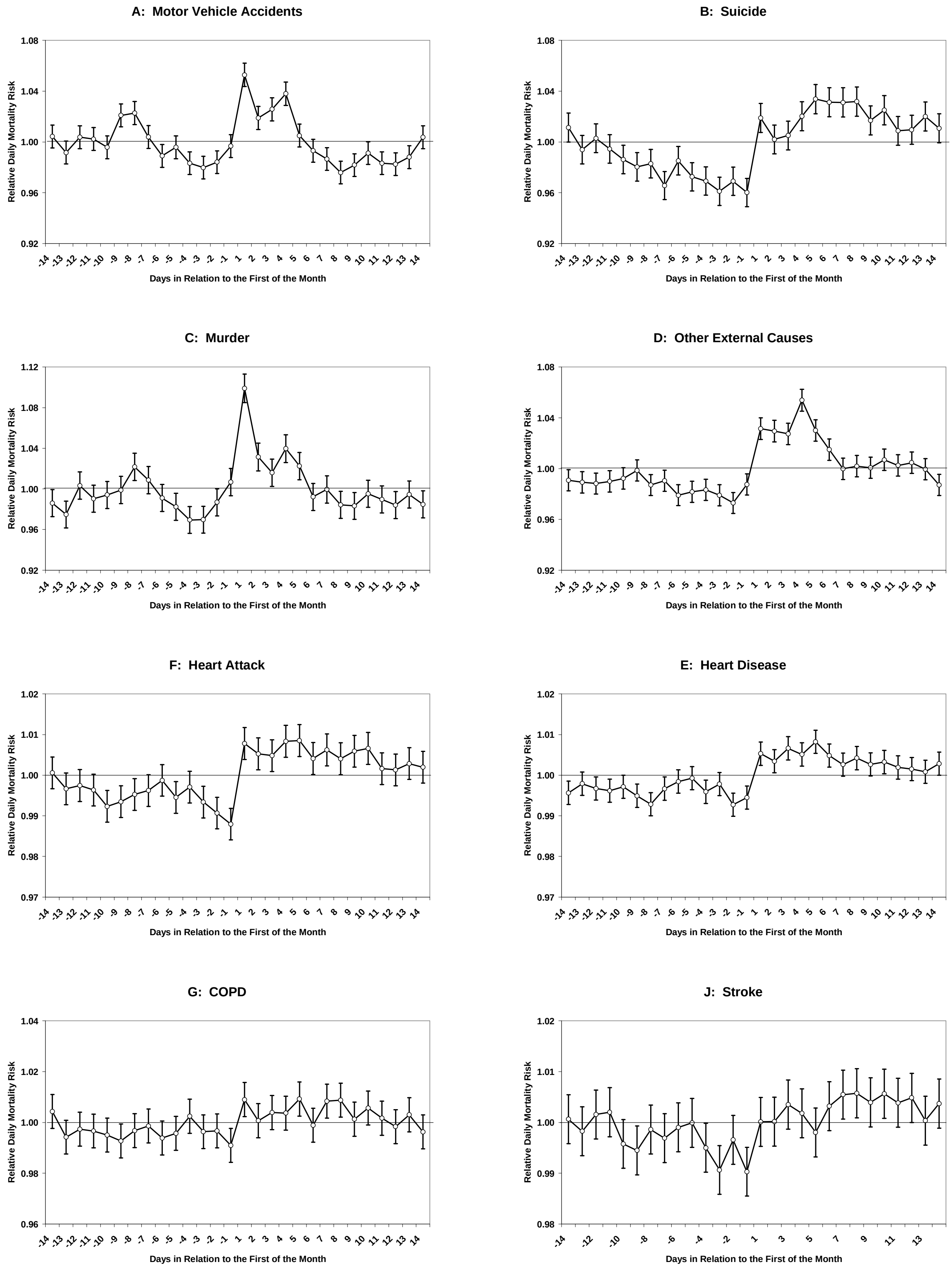
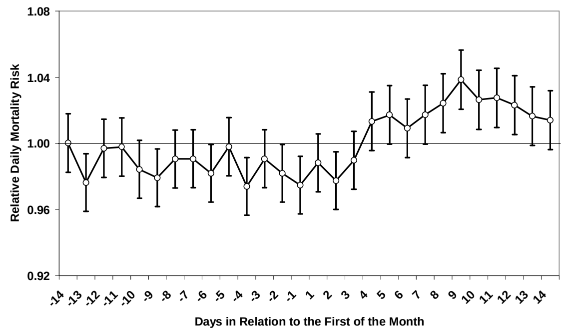


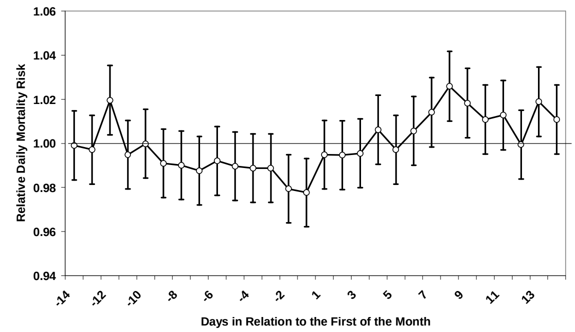
Figure 3: Relative Daily Mortality Rates (95% Confidence Intervals), By Specific Causes, 1973-2005 MCOD



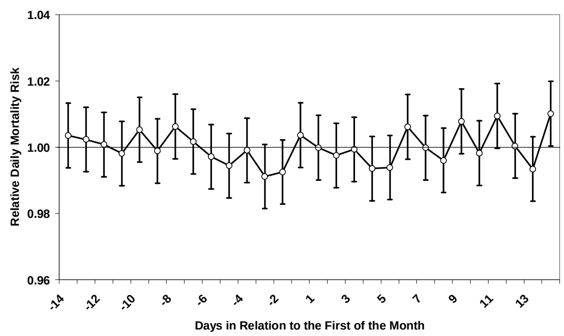
I: Alcohol Cirrhosis



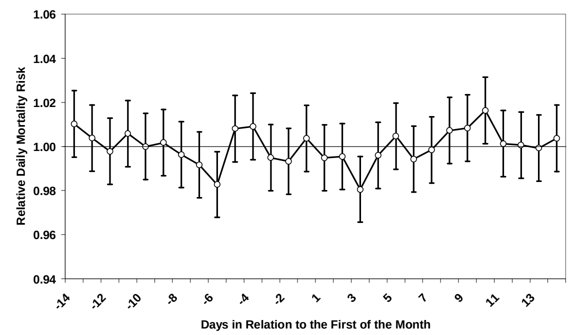
H: Non-Alcohol Cirrhosis



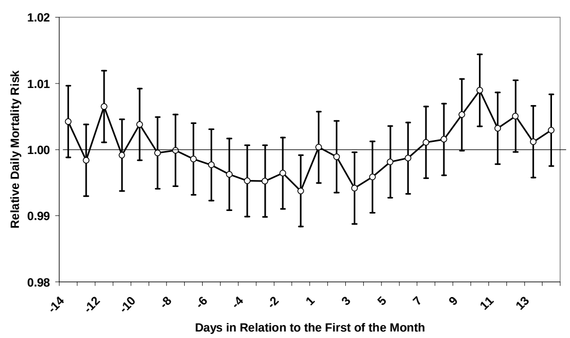
L: Breast Cancer



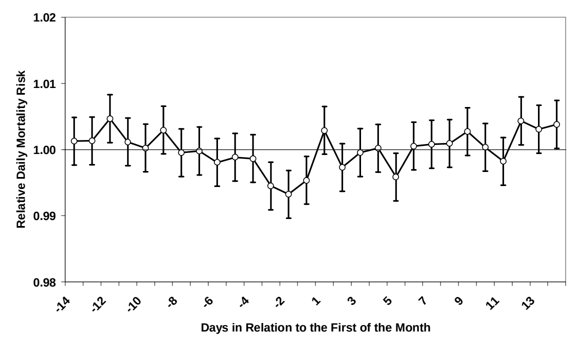
M: Leukemia



K: Lung Cancer



N: Other Cancers



O: Other causes

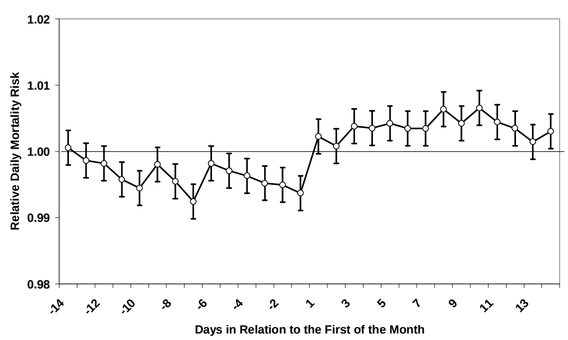


Figure 4: Percent of Fatal Motor Vehicle Accidents with Alcohol Involvement By time of Accident, 1982-2006 FARS

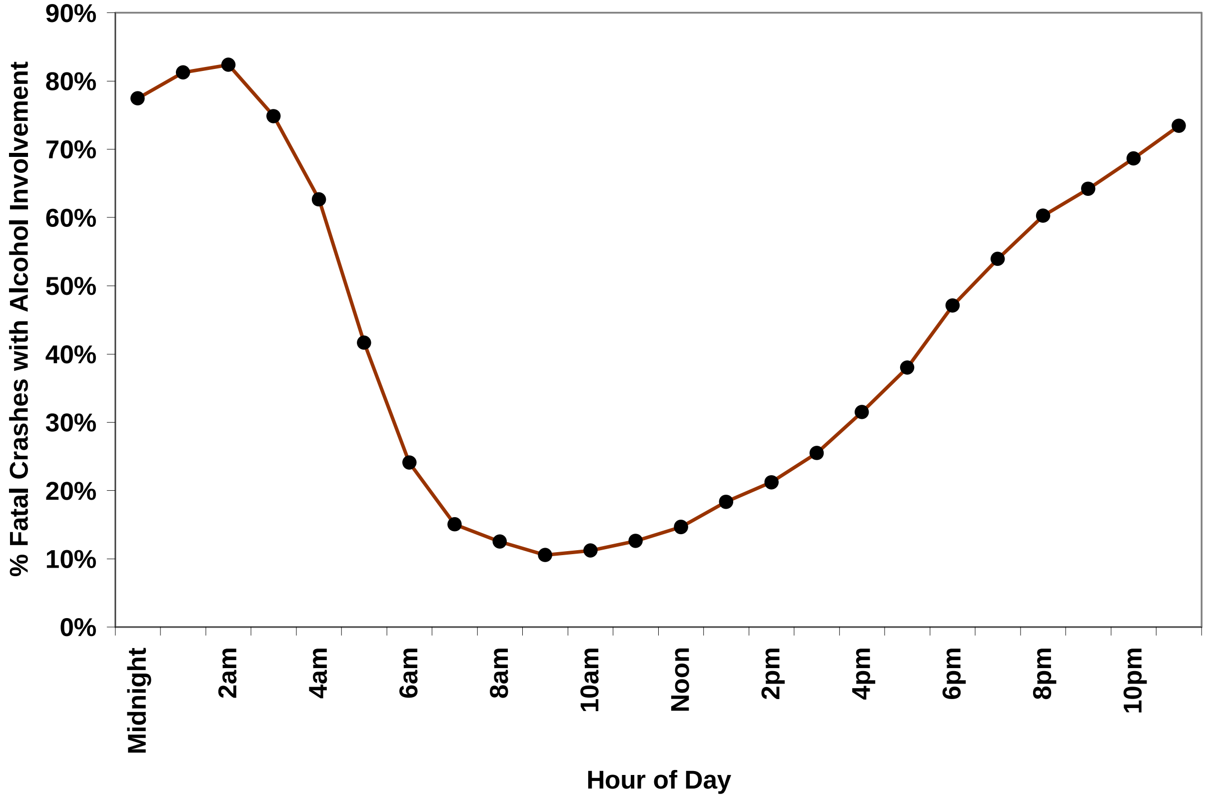


Figure 5: Relative Daily Motor Vehicle Mortality Rates (95% Confidence Inteval), By Specific Causes, 1975-2006 FARS

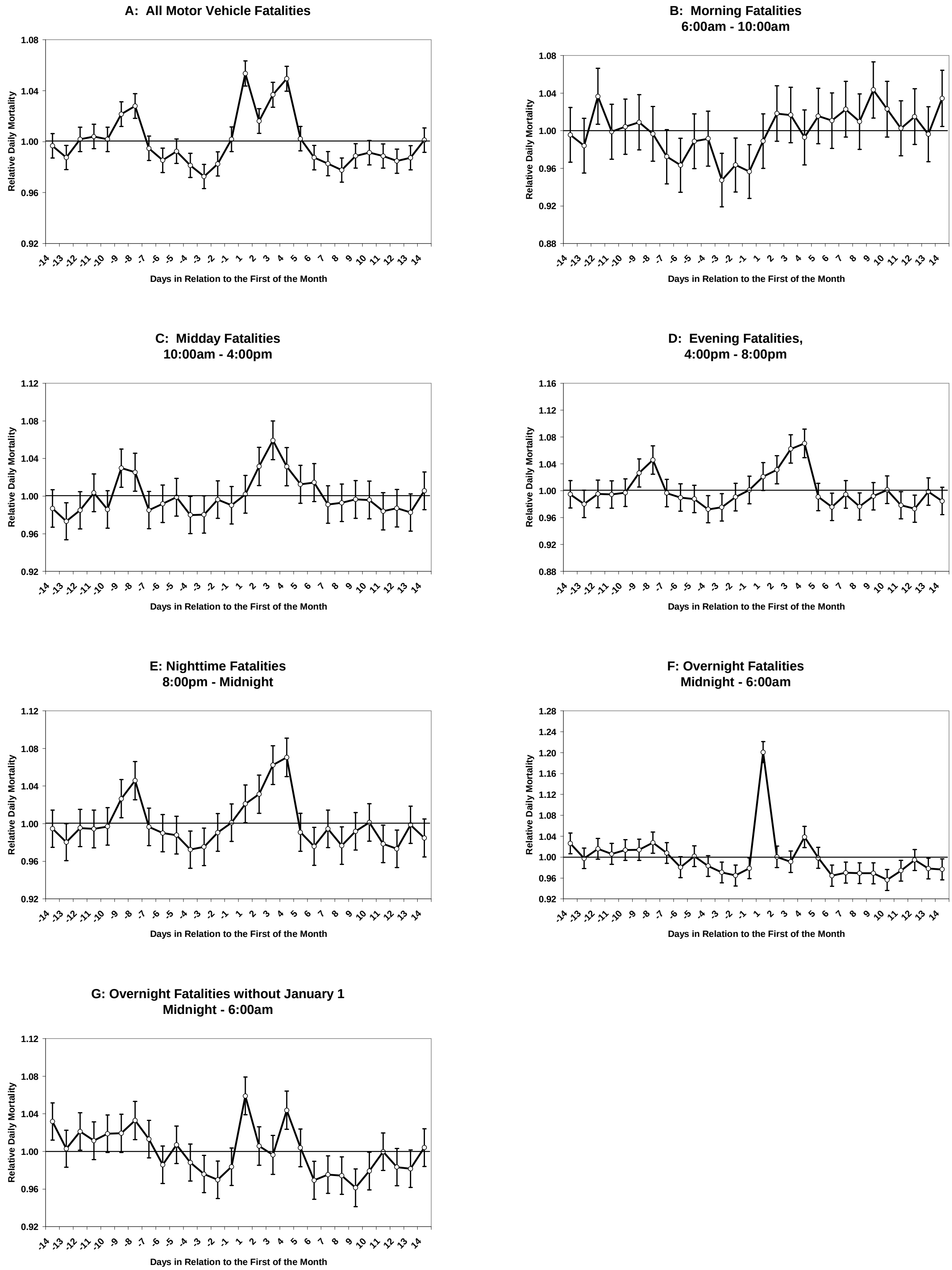
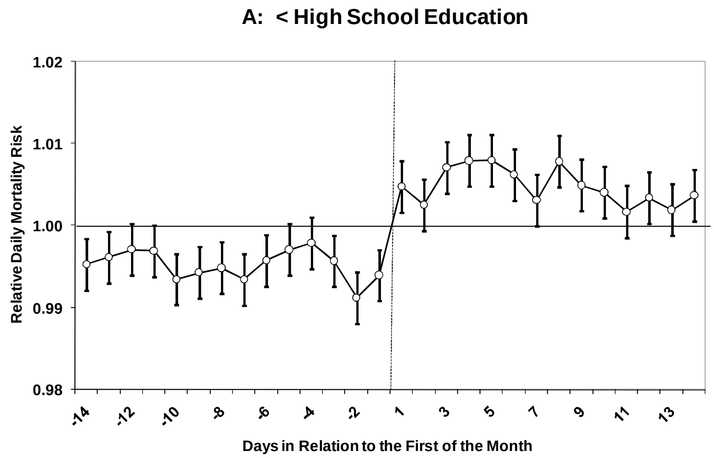
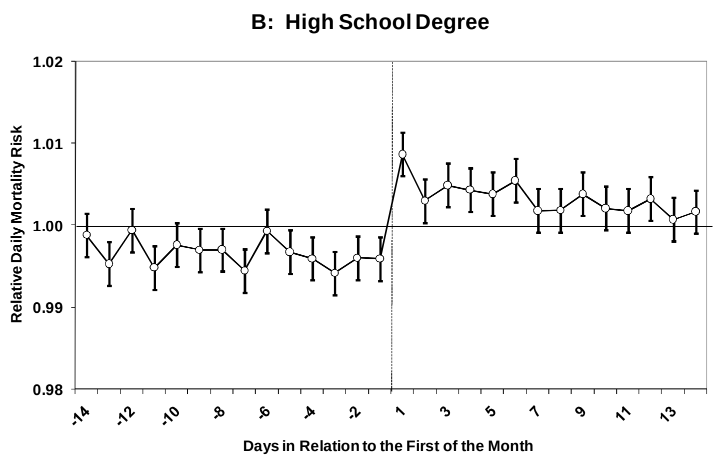


Figure 6: Relative Daily Mortality Rates (95% Confidence Interval), By Education,1989-2005 MCOD





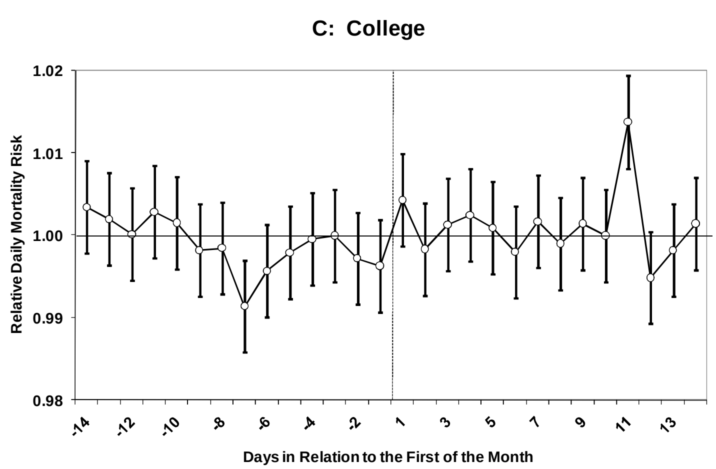


Figure 7: Scatter Plot, Mortality and the Business Cycle versus the Size of the Within-Month Mortality Cycle, By Cause of Death

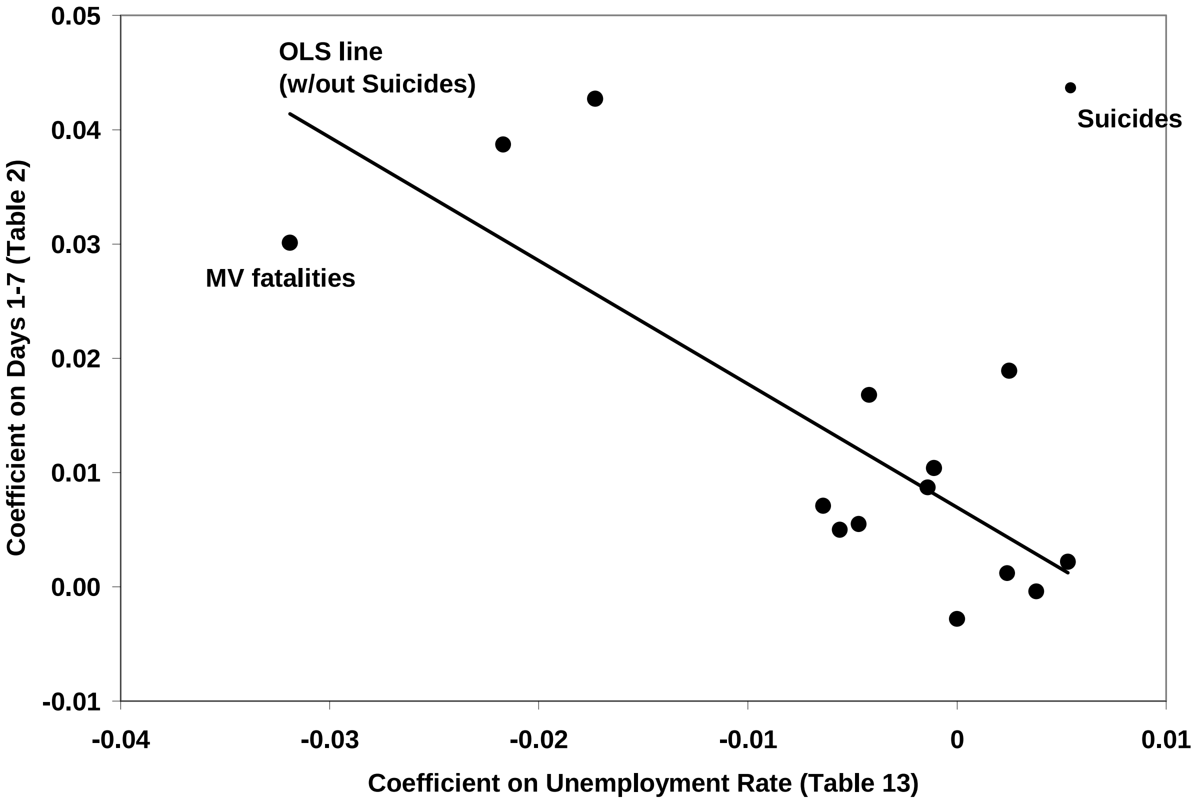


Table 1
OLS Estimates of ln(Daily Mortality Counts), MCOD 1973-2005

OLS estimates of ln(Daily Mortality Counts) R^2=0.0013 (With no other covariates)				OLS estimates of ln(Daily Mortality Counts) R^2=0.9083 (With all covariates)			
Day-14	0.0078	Day 1	0.0133	Day-14	0.0079	Day 1	0.0107
	(0.0021)		(0.0015)		(0.0020)		(0.0012)
Day -13	0.0056	Day 2	0.0096	Day -13	0.0057	Day 2	0.0096
	(0.0020)		(0.0016)		(0.0019)		(0.0014)
Day -12	0.0076	Day 3	0.0114	Day -12	0.0081	Day 3	0.0127
	(0.0020)		(0.0018)		(0.0019)		(0.0016)
Day -11	0.0051	Day 4	0.0133	Day -11	0.0060	Day 4	0.0143
	(0.0020)		(0.0018)		(0.0017)		(0.0015)
Day -10	0.0046	Day 5	0.0121	Day -10	0.0079	Day 5	0.0132
	(0.0019)		(0.0017)		(0.0017)		(0.0015)
Day -9	0.0049	Day 6	0.0104	Day -9	0.0073	Day 6	0.0116
	(0.0017)		(0.0018)		(0.0016)		(0.0016)

Day -8	0.0044	Day 7	0.0110	Day -8	0.0061	Day 7	0.0119
	(0.0015)		(0.0016)		(0.0015)		(0.0016)
Day -7	0.0038	Day 8	0.0115	Day -7	0.0069	Day 8	0.0120
	(0.0017)		(0.0018)		(0.0016)		(0.0016)
Day -6	0.0048	Day 9	0.0110	Day -6	0.0061	Day 9	0.0116
	(0.0017)		(0.0019)		(0.0015)		(0.0016)
Day -5	0.0045	Day 10	0.0123	Day -5	0.0053	Day 10	0.0129
	(0.0017)		(0.0019)		(0.0015)		(0.0017)
Day -4	0.0032	Day 11	0.0107	Day -4	0.0040	Day 11	0.0107
	(0.0016)		(0.0022)		(0.0014)		(0.0020)
Day -3	0.0010	Day 12	0.0099	Day -3	0.0015	Day 12	0.0103
	(0.0015)		(0.0019)		(0.0013)		(0.0017)
Day -2	-0.0003	Day 13	0.0090	Day -2	0.0005	Day 13	0.0097
	(0.0013)		(0.0019)		(0.0011)		(0.0017)
		Day 14	0.0101			Day 14	0.0107
			(0.0018)				(0.0017)
Sun				Sun	-0.0229	Wed.	-0.0258
					(0.0007)		(0.0009)
Mon.				Mon.	-0.0109	Thur.	-0.0258
					(0.0008)		(0.0009)
Tue.				Tue.	-0.0213	Fri.	-0.0121
					(0.0008)		(0.0007)

There are 11,088 observations (336 observations per year for 33 years) and there is an average of 5,931 deaths per day. Numbers in parenthesis are standard errors that allow for arbitrary correlation in the within-month (-14 to 14) errors. Other covariates include synthetic month and year effects plus dummies for special days of the year (New Year's Day, Christmas, etc.). A complete list of days is included in footnote 7.

Table 2
OLS Estimates of ln(Daily Mortality Counts) Model
Demographic Subgroups, 1973-2005

Demographic subgroup	Mean daily Deaths	*Week -2* (*Day -14* to *-7*)	*Week 1* (*Day 1* to *-7*)	*Week 2* (*Day 8* to *14*)	R^2
All deaths	5,938	0.0035	0.0086	0.0077	0.9083
		(0.0011)	(0.0008)	(0.0013)	
Male	3,073	0.0048	0.0114	0.0091	0.8217
		(0.0009)	(0.0009)	(0.0010)	
Female	2,868	0.0030	0.0083	0.0069	0.9340
		(0.0010)	(0.0010)	(0.0010)	
White	5,137	0.0031	0.0064	0.0060	0.8954
		(0.0010)	(0.0010)	(0.0010)	
Black	706	0.0062	0.0235	0.0176	0.8433
		(0.0014)	(0.0015)	(0.0015)	
Other Race	85	0.0025	0.0172	0.0150	0.9245
		(0.0037)	(0.0037)	(0.0037)	
Under 18 years	170	0.0048	0.0077	0.0028	0.8597
		(0.0027)	(0.0024)	(0.0028)	
18 to 39 years	310	0.0097	0.0204	0.0108	0.8003
		(0.0021)	(0.0021)	(0.0021)	
40 to 64 years	1,234	0.0062	0.0161	0.0141	0.7862
		(0.0010)	(0.0010)	(0.0010)	
Over 65 years	4,185	0.0028	0.0056	0.0057	0.9319
		(0.0013)	(0.0011)	(0.0015)	
Single, 1979-2005	753	0.0043	0.0150	0.0087	0.6748
		(0.0015)	(0.0015)	(0.0015)	
Married, 1979-2005	2,540	0.0041	0.0063	0.0067	0.7555
		(0.0010)	(0.0010)	(0.0010)	
Widowed, 1979-2005	2,214	0.0012	0.0063	0.0059	0.9055
		(0.0014)	(0.0014)	(0.0014)	
Divorced, 1979-2005	540	0.0069	0.0214	0.0173	0.9672
		(0.0017)	(0.0017)	(0.0017)	
Metropolitan county	4,311	0.0034	0.0085	0.0073	0.9508
		(0.0010)	(0.0010)	(0.0010)	
Non-metropolitan county	1,609	0.0037	0.0088	0.0083	0.8402
		(0.0012)	(0.0012)	(0.0012)	

All have have 11,088 observations, except for the groups defined by marital status, as this information was not included in the mortality data prior to 1979. These models use 9,408 observations. Numbers in parenthesis are standard errors that allow for arbitrary correlation in the within-month (-14 to 14) errors. Other covariates include synthetic month and year effects plus dummies for special days of the year (New Year's Day, Christmas, etc.). A complete list of days is included in footnote 7.

Table 3
OLS Estimates of ln(Daily Mortality Counts) Model by Substance Abuse, 1979-1998

Cause of death	Years	Mean daily deaths	Week -2 Days -14 to -7	Week 1 Days 1 to -7	Week 2 Days 8 to 14	R^2
All deaths	1979-1998	5,879	0.0037	0.0087	0.0078	0.8763
			(0.0013)	(0.0012)	(0.0015)	
Deaths with a substance abuse multiple cause	1979-1998	257	0.0108	0.0295	0.0141	0.5989
			(0.0028)	(0.0026)	(0.0029)	
Deaths without a substance abuse multiple cause	1979-1998	5,622	0.0034	0.0077	0.0076	0.8824
			(0.0014)	(0.0012)	(0.0016)	

All models have 6,720 observations. Numbers in parenthesis are standard errors that allow for arbitrary correlation in the within-month (-14 to 14) errors. Other covariates include synthetic month and year effects plus dummies for special days of the year (New Year's Day, Christmas, etc.). A complete list of days is included in footnote 7.

Table 4
OLS Estimates of Log Daily Mortality Counts, 1973-2005

Cause of death	Mean daily deaths	Percent substance abuse	Week -2	Week 1	Week 2	R^2
All deaths	5,938	4.37%	0.0035	0.0086	0.0077	0.908
			(0.0011)	(0.0008)	(0.0013)	
			By Cause of Death			
Motor vehicle	127.6	43.02%	0.0152	0.0301	0.0106	0.753
			(0.0037)	(0.0023)	(0.0039)	
Suicides	81.1	14.44%	0.0205	0.0436	0.0397	0.381
			(0.0035)	(0.0038)	(0.0037)	
Homicides	58.0	79.80%	0.0105	0.0387	0.0107	0.591
			(0.0046)	(0.0047)	(0.0049)	
Other external causes	147.0	22.26%	0.0125	0.0427	0.0238	0.655
			(0.0035)	(0.0036)	(0.0041)	
Heart disease	1268.6	0.52%	0.0013	0.0087	0.0060	0.866
			(0.0016)	(0.0014)	(0.0017)	
Heart attack	678.0	0.19%	0.0031	0.0104	0.0067	0.956
			(0.0016)	(0.0016)	(0.0018)	
COPD	231.8	0.44%	0.0020	0.0055	0.0033	0.937
			(0.0028)	(0.0026)	(0.0032)	
Cirrhosis	42.3	0.42%	0.0135	0.0168	0.0269	0.418
			(0.0048)	(0.0049)	(0.0046)	
Alcohol Cirrosis	33.3	100%	0.0076	0.0189	0.0387	0.128
			(0.0051)	(0.0052)	(0.0052)	
Stroke	445.0	0.37%	0.0039	0.0050	0.0062	0.832
			(0.0017)	(0.0017)	(0.0020)	
Lung cancer	353.9	0.12%	0.0036	0.0022	0.0075	0.938
			(0.0019)	(0.0018)	(0.0018)	
Breast cancer	109.4	0.06%	0.0034	-0.0004	0.0019	0.521
			(0.0028)	(0.0030)	(0.0028)	
Leukemia	50.3	0.14%	0.0032	-0.0028	-0.0061	0.446
			(0.0045)	(0.0043)	(0.0042)	
Other cancers	794.5	0.19%	0.0033	0.0012	0.0042	0.913
			(0.0012)	(0.0013)	(0.0012)	
Other conditions	1517.5	4.49%	0.0025	0.0071	0.0078	0.953
			(0.0016)	(0.0014)	(0.0019)	

All models have 11,088 observations. Numbers in parenthesis are standard errors that allow for arbitrary correlation in the within-month (-14 to 14) errors. Other covariates include synthetic month and year effects plus dummies for special days of the year (New Year's Day, Christmas, etc.). A complete list of days is included in footnote 7.The percentage of substance abuse is calculated using deaths between 1979 and 1998.

Table 5
OLS Estimates of Log Daily Motor Vehicle Fatality Count Model,
Fatal Accident Reporting System, 1975-2004

Cause of death	Mean daily Deaths	Week #1 (Days -14, -7)	Week #3 (Days 1 to 7)	Week #4 (Days 8 to 14)	R^2
All motor vehicle fatalities	120.4	0.0164	0.0342	0.0139	0.753
		(0.0042)	(0.0039)	(0.0044)	
Midnight -6:00am	27.4	0.0348	0.0346	0.0190	0.793
		(0.0094)	(0.0087)	(0.0092)	
6:00am-10:00am	12.9	0.0093	0.0281	0.0220	0.232
		(0.0111)	(0.0105)	(0.0108)	
10:00am-4:00pm	26.3	0.0120	0.0460	0.0163	0.301
		(0.0072)	(0.0073)	(0.0073)	
4:00pm-8:00pm	27.6	0.0094	0.0413	0.0103	0.369
		(0.0075)	(0.0075)	(0.0079)	
8:00pm-Midnight	25.3	0.0205	0.0321	0.0112	0.640
		(0.0085)	(0.0085)	(0.0086)	

All models have 10,008 observations (28 observations/month x 12 months x 30 years). Numbers in parenthesis are standard errors that allow for arbitrary correlation in the within-month (-14 to 14) errors. Other covariates include synthetic month and year effects plus dummies for special days of the year (New Year's Day, Christmas, etc.). A complete list of days is included in footnote 7.

Table 6
OLS Estimates of Log Daily Mortality Counts, 1973-2005 MCOD

Covariate	Motor vehicle fatalities	Murders	Other external causes	Suicides
Sunday	0.315	0.251	0.078	-0.120
	(0.006)	(0.006)	(0.004)	(0.005)
Tuesday	-0.033	-0.032	-0.009	-0.066
	(0.004)	(0.006)	(0.004)	(0.004)
Wednesday	-0.013	-0.048	-0.009	-0.098
	(0.005)	(0.006)	(0.004)	(0.004)
Thursday	0.031	-0.032	-0.005	-0.118
	(0.005)	(0.006)	(0.004)	(0.004)
Friday	0.238	0.080	0.034	-0.127
	(0.005)	(0.006)	(0.004)	(0.004)
Saturday	0.452	0.329	0.143	-0.157
	(0.007)	(0.008)	(0.004)	(0.004)
New Year's Day	0.372	0.551	0.203	0.213
	(0.040)	(0.034)	(0.021)	(0.024)
Holy Thursday	0.135	0.088	0.050	-0.019
	(0.021)	(0.026)	(0.017)	(0.021)
Good Friday	0.077	0.055	0.036	-0.028
	(0.016)	(0.025)	(0.019)	(0.018)
Memorial Day	0.151	0.063	0.119	-0.131
	(0.022)	(0.025)	(0.025)	(0.018)
July 4th	0.222	0.214	0.219	-0.096
	(0.022)	(0.040)	(0.021)	(0.019)
Labor Day	0.165	0.151	0.084	-0.171
	(0.016)	(0.025)	(0.018)	(0.019)
Thanksgiving	0.206	0.165	0.028	-0.162
	(0.026)	(0.027)	(0.019)	(0.019)
Christmas Eve	0.374	0.215	0.027	-0.168
	(0.048)	(0.038)	(0.027)	(0.028)
Christmas Day	0.071	0.188	0.009	-0.123
	(0.039)	(0.035)	(0.025)	(0.031)
New Year's Eve	0.371	0.179	0.001	-0.020
	(0.040)	(0.032)	(0.003)	(0.027)

There are 11,088 observations (336 observations per year for 33 years). Numbers in parenthesis are standard errors that allow for arbitrary correlation in the within-month (-14 to 14) errors. Other covariates include synthetic month and year effects, other dummies for special days of the year which are not reported in this table, plus the other coefficients from the model reported in the final two columns of Table 1. A complete list of days is included in footnote 7.

Table 7
OLS Estimates of Daily Consumption Equations,
1996-2004 Consumer Expenditure Survey Diary Data File

	By Types of Items Purchased		
Variable	All food	Non food	All
Week 1	-0.028	0.010	-0.048
	(0.051)	(0.064)	(0.092)
Week 3	0.130	0.077	0.231
	(0.051)	(0.065)	(0.091)
Week 4	0.087	0.101	0.156
	(0.057)	(0.070)	(0.102)
Mean of dep. var.	7.32	6.00	13.22

There are 715, 213 observations in the models. Standard errors are in parenthesis and allow for within-person correlation in errors. Other covariates include complete set of dummy variables for age, sex, race, and the education of reference person, a complete set of dummies for region, urban area and income of the family, plus dummies for the weekday, month, and year, plus dummies for special days during the year. A complete list of days is included in footnote 7.

Table 8
OLS Estimates of the Within-Month Purchase Cycle, Various Sources

Outcome	Time Period	Obs.	Mean daily counts	Week #1 (Days -14, -7)	Week #3 (Days 1 to 7)	Week #4 (Days 8 to 14)	R^2
Ticket sales, MD pick 3 and pick 4	1/1/2003 – 12/31/2006	1,344	0.81 million	0.0065 (0.0055)	0.0705 (0.0047)	0.0319 (0.0041)	0.924
Ticket sales, OH daily number + pick 4	6/20/2005- 6/16/2007	573	1.76 million	0.0121 (0.0071)	0.0875 (0.0061)	0.0388 (0.0061)	0.840
Visits to malls	1/1/2000- 12/22/2007	2,657	25.4 million	0.0375 (0.0087)	0.0207 (0.0079)	0.0314 (0.0079)	0.895
Visits to retail establishments	1/4/2004- 12/22/2007	1,328	94.1 Million	0.0573 (0.0205)	0.0307 (0.0144)	0.0193 (0.0162)	0.851
Visits to apparel retailers	1/4/2004- 12/22/2007	1,325	60.4 million	0.0578 (0.0175)	0.0328 (0.0148)	0.0225 (0.0152)	0.850
Ticket sales top 10 grossing movies	1/1/1998- 6/7/2007	3,171	19.3 million	-0.0057 (0.0237)	0.0558 (0.0192)	-0.0057 (0.0237)	0.928
Attendance at baseball games	1973-1998 2000-2004	54,939	24,238	0.0036 (0.0049)	0.0013 (0.0052)	0.0337 (0.0059)	0.872
DC Metro ridership	1/1/1997 – 9/19/2007	3,573	480,898	0.0015 (0.0070)	0.0009 (0.0069)	0.0078 (0.0069)	0.941

Numbers in parenthesis are standard errors that allow for arbitrary correlation in the within-month (-14 to 14) errors. Other covariates include synthetic month and year effects plus dummies for special days of the year (New Year's Day, Christmas, etc.). A complete list of days is included in footnote 7. Please see the text for any other characteristics of specific models.

Table 9
OLS Estimates of Daily Consumption Equations,
1996-2004 Consumer Expenditure Survey Diary Data File

Variable	Reference person < HS education (N=109,069)			Reference person HS education or some college (N=349,915)			Reference person has associate degree or high (N=256,229)		
Week 1	0.013	0.096	-0.037	0.234	0.206	0.417	0.129	0.264	0.402
	(0.111)	(0.127)	(0.192)	(0.063)	(0.080)	(0.115)	(0.087)	(0.119)	(0.164)
Week 3	0.473	0.084	0.565	0.306	0.238	0.544	-0.033	0.120	0.135
	(0.113)	(0.120)	(0.187)	(0.065)	(0.081)	(0.117)	(0.087)	(0.117)	(0.167)
Week 4	0.182	0.100	0.240	0.247	0.257	0.480	0.172	0.244	0.361
	(0.122)	(0.135)	(0.213)	(0.071)	(0.088)	(0.131)	(0.097)	(0.128)	(0.182)
Mean of dep. var.	5.88	3.99	9.97	6.88	5.60	12.48	8.51	7.39	15.90
	Households with any non-SS federal support income (n=34,372)			Households with SS income but no other federal support income (n=130,239)			Households with no SS income and no federal support income (n=550,602)		
Week 1	-0.108	-0.039	-0.029	0.098	-0.010	-0.029	-0.049	0.022	-0.044
	(0.216)	(0.251)	(0.172)	(0.099)	(0.120)	(0.171)	(0.060)	(0.077)	(0.109)
Week 3	1.364	0.285	1.786	0.348	0.254	0.585	0.002	0.025	0.054
	(0.236)	(0.256)	(0.401)	(0.104)	(0.120)	(0.180)	(0.059)	(0.078)	(0.109)
Week 4	0.558	-0.268	0.538	0.123	0.155	0.241	0.052	0.116	0.119
	(0.246)	(0.267)	(0.430)	(0.113)	(0.133)	(0.201)	(0.067)	(0.084)	(0.122)
Mean of dep. var.	6.42	4.42	10.81	6.25	4.50	10.71	7.62	6.45	13.96
	Family income < $30,000 (n=338,890)			Family income ≥$30,000 (n=182,263)			Family income not reported (n=194,060)		
Week 1	0.007	0.017	-0.039	-0.272	-0.213	-0.517	0.119	0.187	0.328
	(0.062)	(0.077)	(0.111)	(0.125)	(0.168)	(0.231)	(0.097)	(0.116)	(0.170)
Week 3	0.267	0.120	0.399	-0.241	0.015	-0.205	0.240	0.048	0.362
	(0.064)	(0.076)	(0.112)	(0.121)	(0.173)	(0.232)	(0.100)	(0.116)	(0.172)
Week 4	0.082	0.064	0.152	0.083	0.047	-0.112	0241	0.187	0.349
	(0.069)	(0.082)	(0.124)	(0.136)	(0.184)	(0.259)	(0.112)	(0.126)	(0.194)
Mean of dep. var.	6.02	4.76	10.74	10.68	9.55	20.02	6.42	4.83	11.11

Standard errors are in parenthesis and allow for within-person correlation in errors. Other covariates include complete set of dummy variables for age, sex, race, and the education of reference person, a complete set of dummies for region, urban area and income of the family, plus dummies for the weekday, month, and year, plus dummies for special days during the year.

Table 10
Negative Binomial Estimates of Daily Mortality Counts, 1988-2005

Group	Mean daily Deaths	Week #1 (Days -14, -7)	Week #3 (Days 1 to 7)	Week #4 (Days 8 to 14)	R^2
All deaths	6,360	0.0015	0.0091	0.0074	0.9344
		(0.0015)	(0.0015)	(0.0015)	
			By level of education		
< High school	1,916	0.0021	0.0102	0.0093	0.7981
		(0.0018)	(0.0018)	(0.0018)	
High school	2,908	0.0008	0.0093	0.0072	0.9610
		(0.0015)	(0.0019)	(0.0015)	
College degree	664	0.0031	0.0045	0.0023	0.9417
		(0.0020)	(0.0020)	(0.0021)	

All models have 5,712 observations. Numbers in parenthesis are standard errors that allow for arbitrary correlation in the within-month (-14 to 14) errors. Other covariates include a complete set of day of the week, monthly and annual dummy variables, plus a complete set of dummies for special days specified in footnote 7.

Table 11
Estimates of Daily Mortality Count Model, Those 65 Years, MCOD 1973-1996

Days Before Social Security Payment		Days After Social Security Payment	
Payday -14	0.0059	Payday 1	0.0059
	(0.0027)		(0.0018)
Payday -13	0.0011	Payday 2	0.0080
	(0.0028)		(0.002)
Payday -12	0.002	Payday 3	0.0064
	(0.0024)		(0.0021)
Payday -11	0.0052	Payday 4	0.0051
	(0.0022)		(0.0021)
Payday -10	0.0006	Payday 5	0.0054
	(0.0023)		(0.002)
Payday -9	0.0024	Payday 6	0.0072
	(0.0023)		(0.002)
Payday -8	0.0025	Payday 7	0.0055
	(0.0021)		(0.0021)
Payday -7	0.0017	Payday 8	0.0072
	(0.0022)		(0.0024)
Payday -6	0.0006	Payday 9	0.0052
	(0.002)		(0.0023)
Payday -5	-0.0008	Payday 10	0.0059
	(0.002)		(0.0021)
Payday -4	-0.0018	Payday 11	0.0049
	(0.0021)		(0.0024)
Payday -3	-0.0055	Payday 12	0.0054
	(0.0018)		(0.0024)
Payday -2	0.0005	Payday 13	0.0063
	(0.0018)		(0.0029)
		Payday 14	0.0065
			(0.0029)
Sun	-0.0159	Wed.	-0.0053
	(0.0011)		(0.0012)
Mon.	0.0099	Thur.	-0.0067
	(0.0011)		(0.0011)
Tue.	0.0017	Fri.	-0.0003
	(0.0011)		(0.0009)

There are 7,488 observations. The average number of all deaths for ages over 65 years is 3,947 per day. Numbers in parenthesis are standard errors that allow for arbitrary correlation in the within-month (-14 to 14) errors. Other covariates include a complete set of day of the week, monthly and annual dummy variables, plus a complete set of dummies for special days specified in footnote 7.

Table 12

OLS Estimates of ln(Counts) in Relation to Social Security Payment Schedule, MCOD Ages 65 to 69

1992 to 1996: Old SS Schedule $R^2 = 0.6098$, N = 1,680				2001 to 2005: Old SS Schedule $R^2 = 0.5848$, N = 1,680				2001 to 2005: New SS Schedule $R^2 = 0.2112$, N = 5,037			
Payday coefficients				Payday coefficients				Payday coefficients			
-14	-0.0029	1	0.0157	-14	0.0010	1	-0.0018			1	0.0023
	(0.0087)		(0.0071)		(0.0076)		(0.0071)				(0.0086)
-13	-0.0038	2	0.0231	-13	-0.0022	2	0.0016			2	-0.0002
	(0.0084)		(0.0070)		(0.0073)		(0.0081)				(0.0086)
-12	0.0030	3	0.0180	-12	-0.0234	3	-0.0041			3	0.0031
	(0.0091)		(0.0084)		(0.008)		(0.0089)				(0.0087)
-11	0.0071	4	0.0139	-11	-0.0045	4	-0.0043			4	0.0014
	(0.0086)		(0.0078)		(0.0072)		(0.008)				(0.0087)
-10	0.0022	5	0.0078	-10	-0.0044	5	-0.0038			5	-0.0023
	(0.0088)		(0.0084)		(0.0072)		(0.0089)				(0.0087)
-9	0.0199	6	0.0118	-9	-0.0239	6	-0.0081			6	-0.0183
	(0.0084)		(0.0082)		(0.0081)		(0.0081)				(0.0087)
-8	0.0128	7	0.0242	-8	-0.0116	7	-0.0037	-8	0.0009	7	-0.0050
	(0.0091)		(0.0066)		(0.0078)		(0.0087)		(0.0086)		(0.0086)
-7	-0.0008	8	0.0098	-7	-0.0159	8	-0.0122	-7	0.0035	8	-0.0084
	(0.009)		(0.0075)		(0.0076)		(0.0093)		(0.0086)		(0.0086)
-6	0.0024	9	0.0098	-6	-0.0146	9	-0.0145	-6	0.0015	9	-0.0114
	(0.0076)		(0.0081)		(0.0087)		(0.0088)		(0.0086)		(0.0086)
-5	-0.0102	10	0.0113	-5	-0.018	10	-0.0155	-5	0.0024	10	0.0011
	(0.0083)		(0.0081)		(0.0071)		(0.0088)		(0.0086)		(0.0086)
-4	-0.0009	11	0.0148	-4	0.0036	11	-0.0125	-4	-0.0063	11	0.0135
	(0.0077)		(0.0076)		(0.0078)		(0.0085)		(0.0086)		(0.0086)
-3	-0.0142	12	0.0032	-3	-0.0104	12	-0.0094	-3	-0.0077	12	-0.0106
	(0.0072)		(0.0085)		(0.0078)		(0.0086)		(0.0086)		(0.0087)
-2	0.0015	13	0.0140	-2	-0.0028	13	-0.007	-2	-0.0056	13	-0.0014
	(0.0078)		(0.0109)		(0.0086)		(0.0083)		(0.0086)		(0.0087)
		14	0.0067			14	-0.009			14	-0.0152
			(0.0089)				(0.0084)				(0.0086)
Weekday coefficients				Weekday coefficients				Weekday coefficients			
Su	-0.0221	W	-0.0035	Su	-0.024	W	-0.0027	Su	-0.0159	W	0.0027
	(0.0052)		(0.0048)		(0.0055)		(0.0049)		(0.0088)		(0.0087)
Mo	0.0122	Th	0.0022	Mo	0.0046	Th	-0.0031	Mo	0.0176	Th	0.0051
	(0.0048)		(0.005)		(0.0044)		(0.0044)		(0.0088)		(0.0087)
Tu	0.0026	Fr	0.0127	Tu	0.0027	Fr	0.0082	Tu	0.0095	Fr	0.0125
	(0.0045)		(0.0046)		(0.0042)		(0.0044)		(0.0087)		(0.0088)

The average number of deaths amongst those aged 65 to 69 years from 1992 to 1996 is 568 per day, and the average number of deaths for ages 65 to 69 between 2001 and 2005 is 479 per day. Numbers in parenthesis are standard errors that allow for arbitrary correlation in the within-payment month (-14 to 14) errors. Other covariates include a complete set of day of the week, monthly and annual dummy variables, plus a complete set of dummies for special days specified in footnote 7.

Table 13
OLS Estimates of State-Level ln(Cause-Specific Death Rate) Equation,
50 States and the District of Columbia, 1976-2004.

Cause of death	Deaths per 100,000 people	Coefficient (Standard error) on state-level unemployment	R2
All deaths	869.1	-0.0039	0.968
		(0.0013)	
	By causes of death		
Motor vehicle accidents	21.3	-0.0319	0.930
		(0.0043)	
Suicides	12.9	0.0146	0.886
		(0.0059)	
Homicides	7.9	-0.0217	0.907
		(0.0080)	
Other external causes	23.9	-0.0175	0.803
		(0.0049)	
Non-AMI heart disease	177.3	-0.0014	0.919
		(0.0026)	
AMI	102.9	-0.0113	0.963
		(0.0038)	
COPD	33.8	-0.0046	0.963
		(0.0024)	
Cirrhosis, non-alcohol related	5.9	-0.0042	0.819
		(0.0079)	
Cirrhosis, alcohol related	4.9	0.0026	0.826
		(0.0092)	
Stroke	66.7	-0.0056	0.948
		(0.0032)	
Lung cancer	50.3	0.0054	0.958
		(0.0019)	
Breast cancer	15.6	0.0039	0.910
		(0.0018)	
Leukemia	7.3	-0.0000	0.845
		(0.0018)	
Other cancers	115.4	0.0024	0.968
		(0.0012)	
All other causes	223.0	-0.0064	0.941
		(0.0020)	

All models have data from 50 states and the District of Columbia over the 29 year period 1976-2004. The dependent variable is the log death rate (deaths per 100,000 people). All models control for state and year effects plus the fraction black, fraction under 5 years of age and the fraction over 64 years of age. Observations are weighted by population. The standard errors are calculated allowing for arbitrary correlation in errors within a state.