LIQUIDITY, ECONOMIC ACTIVITY, AND MORTALITY

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Abstract—We document a within-month mortality cycle where deaths decline before the first day of the month and spike after the first. This cycle is present across a wide variety of causes and demographic groups. A similar cycle exists for a range of economic activities, suggesting the mortality cycle may be due to short-term variation in levels of economic activity. We provide evidence that the within-month activity cycle is generated by liquidity. Our results suggest a causal pathway whereby liquidity problems reduce activity, which in turn reduces mortality. These relationships may help explain the procyclical nature of mortality.

I. Introduction

DAILY mortality counts fluctuate over the course of a calendar month, decreasing by about 1% below the average in the week prior to the first day of the month and then increasing to almost 1% above the average in the first few days of the month (Phillips, Christenfeld, & Ryan, 1999). This within-month mortality cycle is particularly pronounced for suicides, homicides, and accidents. Phillips et al. speculate that this cycle may be driven in part by substance abuse, since "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" (p. 97). Subsequent work has focused almost exclusively on the role that substance abuse plays in explaining this within-month pattern (Verhuel, Singer, & Christenson, 1997; Maynard & Cox, 2000; Halpern & Mechem, 2001; Swartz, Hsieh, & Baumohl, 2003; Riddell & Riddell, 2006; & Li et al., 2007). In the most detailed study to date, Dobkin and Puller (2007) use administrative records from California to show there is a within-month cycle for hospital admissions of Supplemental Security Income recipients, with the cycle particularly pronounced for substance abuse admissions.[1]

Although Phillips et al. (1999) document a within-month cycle for deaths not classified as due to substance abuse, none of the existing studies have considered an explanation outside the transfer payment–substance abuse nexus. In this paper, we show that the within-month mortality cycle is a more general phenomenon than is currently understood. Although the peak-to-trough of the within-month cycle is large in percentage terms for substance abuse deaths, these deaths account for a minority of the overall pattern. Updating and extending the earlier work of Phillips et al., we document within-month mortality cycles for many causes of death, including external causes, heart disease, heart attack, and stroke, but not cancer. The within-month cycle is also evident for both sexes and for all age groups, races, marital status groups, and education groups.

The broad-based nature of the within-month mortality cycle leads us to examine whether these cyclic patterns are present for various types of economic activity. 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 to the movies, and the amounts spent on food and nonfood retail purchases. These data all show the same pattern: that economic activity declines toward the end of the month and rebounds after the first of the month.

The concordance between the mortality and activity cycles leads us to conclude that an increase in economic activity after the first of the month leads to the increase in mortality. For some causes of death, this link is obvious: one cannot die in a traffic accident unless one is in traffic. While it is not so obvious for other causes of death, it is well documented in the medical literature that certain types of consumption, such as eating heavy meals, and activity, such as shoveling snow and exercising, are triggers for heart attacks and strokes.

We provide suggestive evidence that the within-month mortality and economic activity cycles are linked to changing liquidity over the month. First, we document that the peak-to-trough in mortality and consumption is largest for people expected to have the greatest liquidity issues, such as those with low levels of education and income and those on federal transfer programs. Second, 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. Finally, we provide direct evidence of a short-term increase in mortality after the receipt of income.

Much of the direct evidence for this last result is provided in a companion paper (Evans & Moore, 2011), where we consider five situations in which we can identify when a group of people received an income payment. In each case, we find that mortality increases immediately after income receipt. One of these situations is the 2001 tax rebate checks, where mortality increased among 25 to 64 year olds by 2.7% in the week after the checks arrived. In this paper, we extend the analysis to show that this mortality effect

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[1] In related work, Foley (2011) finds a different monthly cycle for crimes motivated by financial gain, such as burglary, robbery, and motor vehicle theft. In cities where transfers administered by the state government are paid at the start of the month, these crimes increase in the last few days prior to the first of the month and then decline after the first, a pattern he attributes to the same lack of liquidity toward the end of the month.

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was 5.2% on the three occasions when these checks arrived at the end of the month—when we believe that liquidity issues are most acute—and a 1.6% increase otherwise.

With wages and transfers frequently paid around the first of each month, the apparent link of liquidity, economic activity, and mortality seems to be a consequence of people not smoothing their consumption in accordance with the life cycle–permanent income hypothesis. Many authors have demonstrated that consumption displays excess sensitivity to the arrival of predictable income payments (Wilcox, 1989; Shea, 1995; Parker, 1999; Souleles, 1999; Johnson, Parker, & Souleles, 2006). Our work is most similar to that of Stephens (2003), who found that seniors consume more after receiving Social Security checks, and Stephens (2006), who demonstrates that U.K. workers consume more after payday.

It is not clear how much of this within-month variation is mortality displacement (the timing of deaths is altered by a few weeks) or additional deaths. The fall in deaths in the last few days of the month and the analysis of one-off payments in Evans and Moore (2011) suggests that many of the deaths are being shifted from nearby periods. In any case, there are implications for researchers trying to understand the relationship between economic activity and mortality and also for researchers whose phenomena of interest may be obscured by this pattern.

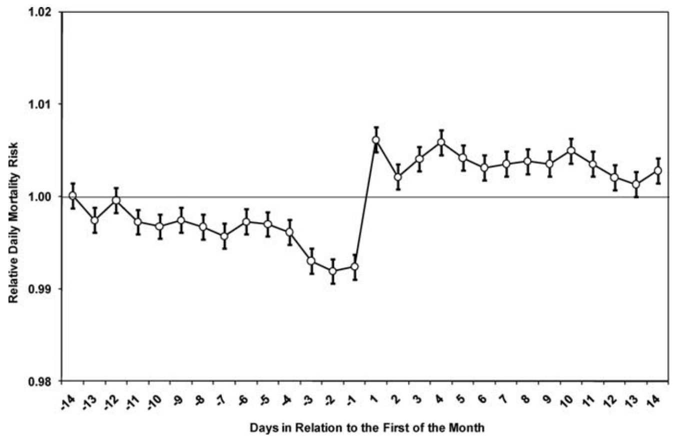
Our work also has implications for a growing literature on mortality over the business cycle. In contrast to a large literature suggesting that higher incomes are protective of health, work by Ruhm (2000) and others suggests that mortality is procyclical, although the reason for this result remains uncertain. In the final section of the paper, we show that the death categories with the greatest peak-to-trough in the within-month mortality cycle are also those categories most strongly tied to the business cycle. This suggests that rising mortality in a boom is produced by the increased levels of personal economic activity generated by a robust economy.

II. Replicating and Expanding the Basic Findings

A. Pooling Samples from 1973 to 2005

The primary data for this analysis are the Multiple Cause of Death (MCOD) data files compiled by the National Center for Health Statistics (NCHS). They contain a unique record of each death occurring in the United States, which includes information about the decedent's age, race, gender, place of residence, and cause of death.[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 is now available only on restricted-use versions of the data.[3] Permission to use the 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.

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



In figure 1, we graph the within-month mortality cycle using deaths for the entire 1973–2005 period. The horizontal axis shows days in relation to the first of the month: *Day 1* is the first.[4] To provide symmetry, we report the fourteen days prior to the first and the first fourteen 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 a particular day, computed as the average deaths on a given day divided by the average deaths across all days. Thus, a value of 1.1 represents a 10% increase in the daily risk of death. The relative risk is represented by the open circles, while the vertical lines from the circles are 95% confidence intervals.[5]

The shape of the graph is similar to that in Phillips et al.[6] Starting about twelve days before the first of the month, daily deaths decline slowly and fall to 0.8% below the average on the day before the first. Deaths then increase on the first of the month to 0.6% above average. The peak-to-trough represents about a 1.4% difference in daily mortality rates. With an average of 5,938 deaths per day in our sample, the increase in deaths from the last day of the month to the first represents 81 deaths per month, or about 970 deaths per year.

[2] 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] As in Phillips et al. (1999), the labeling is . . . , *Day −2*, *Day −1*, *Day 1*, *Day 2*, . . . Not using a 0 allows us to match the *Day 1* to *Day 14* dummy variables with the first fourteen days of the calendar month.

[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 $V[d_t] = N_t p_t(1 - p_t) = \sigma_t^2$. A consistent estimate of p_t is d_t/N_t.

[6] Using data from 1973 to 1988 only, we are able to replicate the basic results in Phillips et al. (1999).

TABLE 1.—OLS ESTIMATES OF LN(DAILY MORTALITY COUNTS) MODEL, MCOD DATA, 1973–2005

Coefficient (Standard Error) on the *Day(j)* Variable							
Day(−14)	0.0079 (0.0020)	*Day(−7)*	0.0069 (0.0016)	*Day(1)*	0.0107 (0.0012)	*Day(8)*	0.0120 (0.0016)
Day(−13)	0.0057 (0.0019)	*Day(−6)*	0.0061 (0.0015)	*Day(2)*	0.0096 (0.0014)	*Day(9)*	0.0116 (0.0016)
Day(−12)	0.0081 (0.0019)	*Day(−5)*	0.0053 (0.0015)	*Day(3)*	0.0127 (0.0016)	*Day(10)*	0.0129 (0.0017)
Day(−11)	0.0060 (0.0017)	*Day(−4)*	0.0040 (0.0014)	*Day(4)*	0.0143 (0.0015)	*Day(11)*	0.0107 (0.0020)
Day(−10)	0.0079 (0.0017)	*Day(−3)*	0.0015 (0.0013)	*Day(5)*	0.0132 (0.0015)	*Day(12)*	0.0103 (0.0017)
Day(−9)	0.0073 (0.0016)	*Day(−2)*	0.0005 (0.0011)	*Day(6)*	0.0116 (0.0016)	*Day(13)*	0.0097 (0.0017)
Day(−8)	0.0061 (0.0015)			*Day(7)*	0.0119 (0.0016)	*Day(14)*	0.0107 (0.0017)

The R^2 for this model is 0.9083. The reference period is *Day(−1)*. There are 11,088 observations (336 observations per year for 33 years) and an average of 5,938 deaths per day. Numbers in parentheses are standard errors that allow for arbitrary correlation in errors within each unique synthetic 28-day month. Other covariates include day-of-the-week effects, synthetic month and year effects, plus dummies for special days of the year (for example, New Year's Day, Christmas). A complete list of days is included in note 7.

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. 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 the 28 days surrounding the first of the month. *Month 1* contains data from December 18 through January 14 of the next year, *Month 2* from January 18 through February 14, and so on. Synthetic years begin fourteen days before the first of January. Given this structure for the data, the econometric model we estimate is

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

where *Day(d)* is a dummy variable equal to 1 if it is day d and 0 otherwise, *Weekday(j)* is one of six dummy variables for the different weekdays, and *Special(j)* is one of J dummy variables for special days throughout the year.[7] The variables μ_m and ν_y capture synthetic month and year effects, and ε_{dmy} is an idiosyncratic error term.[8] The reference day is the day prior to the start of the month (*Day(−1)*), and the reference weekday is Saturday. We estimate standard errors, allowing for arbitrary correlation in errors within each unique 28-day synthetic month.

In table 1, we report estimates for the 27 *Day(d)* coefficients from equation (1) when controlling for all the other covariates listed above. Even with the regression adjustment, we find a large within-month mortality cycle, with daily mortality counts about 1% higher after the start of the month and the estimate has a z-score of 8.9.

To better understand the magnitude of the results in table 1, we alter the model in equation (1) and replace daily dummy variables with dummy variables for weeks in relation to the first of the month. We include three 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 period is the week before the first of the month (*Week(−1)*).

Results for this model are listed in the top row of table 2. Mortality is 0.9% higher in the first week of the month than in the preceding week, and this result has a z-score of about 10.7. On average, over a year, the first week of the month has about 4,324 more deaths than the previous week.

B. *Does the Within-Month Cycle Extend Past Substance Abuse–Related Deaths?*

We now examine how much of the within-month cycle is due to substance abuse. Each observation in the MCOD data has up to twenty causes of death, coded according to the International Classification of Disease (ICD) codes. During our period of analysis, the MCOD used three versions of the ICD codes: ICD-8 (1973–1978), ICD-9 (1979–1998), and ICD-10 (1999–2005). In this section, we focus on when the ICD-9 coding system was used, as the specificity of the codes for identifying substance abuse varies substantially across the three versions.

Given that our primary concern is to examine the mortality cycle for deaths unrelated to substance abuse, we err on the side of including too many deaths in the substance

[7] We include unique dummies for a list of reoccurring special days, including January 1 and 2, the Friday through Monday associated with all federal holidays occurring on Mondays (Presidents' Day, Martin Luther King Jr. Day since 1986, Memorial Day, Labor Day, and Columbus Day), Super Bowl Sunday and the following Monday, Holy Thursday through Easter Sunday, July 4, Veterans Day, the Monday to Sunday of the week of Thanksgiving, a dummy for the days from the day after Thanksgiving to New Year's Eve, plus single-day dummies for December 24 through December 31. We also reduce the number of homicides on September 11, 2001, by 2,902 deaths, which, according to a Centers for Disease Control report, was the number of deaths on that date due to the terrorist attacks (the report is available at 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] The results throughout the paper are similar when we interact the month and year dummy variables.

TABLE 2.—OLS ESTIMATES OF LN(DAILY MORTALITY COUNTS) MODEL BY CAUSE OF DEATH, MCOD DATA, 1979–1998

Cause of Death	Years	Mean Daily Deaths	*Week(−2)*	*Week(1)*	*Week(2)*	R^2
All deaths	1973–2005	5,938	0.0035 (0.0011)	0.0086 (0.0008)	0.0077 (0.0013)	0.908
All deaths	1979–1998	5,879	0.0037 (0.0013)	0.0087 (0.0012)	0.0078 (0.0015)	0.876
Deaths with a substance abuse multiple cause	1979–1998	257	0.0108 (0.0028)	0.0295 (0.0026)	0.0141 (0.0029)	0.599
Deaths without a substance abuse multiple cause	1979–1998	5,622	0.0034 (0.0014)	0.0077 (0.0012)	0.0076 (0.0016)	0.882

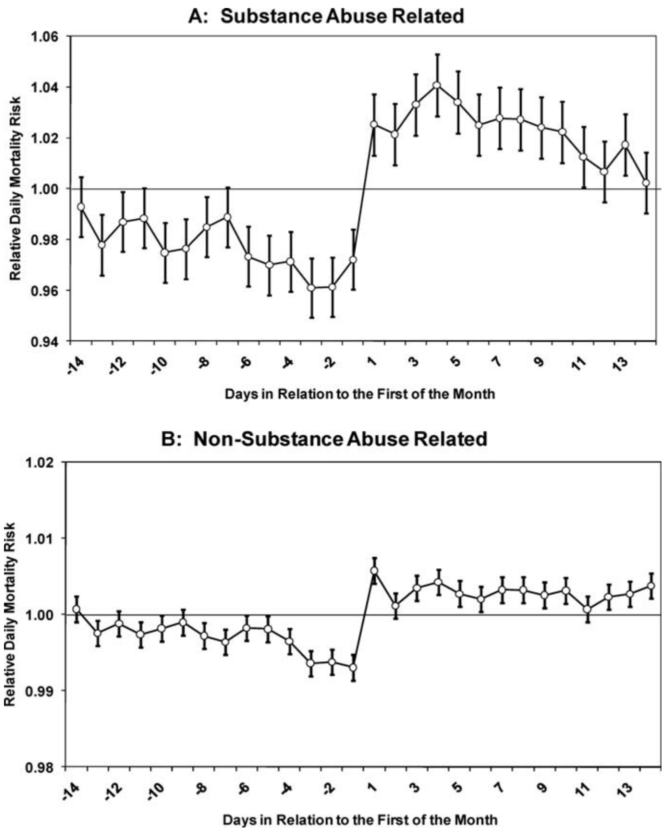
The reference period is *Week(−1)*. All models have 6,720 observations, except for the model in the first row, which has 11,088 observations. Numbers in parentheses are standard errors that allow for arbitrary correlation in errors within each unique synthetic 28-day month. Other covariates include synthetic month and year effects plus dummies for special days of the year (for example, New Year's Day, Christmas). A complete list of days is included in note 7.

abuse category rather than too few. Phillips et al. (1999) define a death as substance abuse related if it has a primary or secondary cause related to alcohol or drug use.[9] We expand this definition in two ways. First, we use a broader set of ICD-9 codes to identify substance abuse by adding conditions attributable to alcohol or drugs contained in studies on the economic costs of substance abuse in the United States (Harwood, Fountain, & Livermore, 1998), Australia (Collins & Lapsley, 2002), and Canada (Single et al., 1999).[10] Second, a death is classified as a substance abuse death if these codes are listed as any of the twenty causes rather than just the first two. As a result of our broader definition of substance abuse, we define a far higher proportion of deaths as related to substance abuse (4.3%) compared to Phillips et al. (1.7%).

Figure 2 contains the relative daily mortality rates for deaths related to substance abuse (in panel A) and deaths not related to substance abuse (panel B). There is a large peak-to-trough for substance abuse deaths. For the four days prior to the first of the month, deaths are about 2% below the daily average, before spiking on *Day(1)* to 4% above the daily average. Panel B contains the results for deaths not related to substance abuse. The magnitude of the within-month cycle for this sample is nearly identical to the graph for all deaths in figure 1. The trough occurs on *Day(−1)*, and the peak occurs on *Day(1)*, with a difference of more than 1%. The cycle present in figure 1 is not caused solely by substance abuse.

These patterns remain once we estimate the model using the natural log of fatality counts regressed on weekly dummies and the various controls contained in equation (1). The second row of table 2 contains the coefficients on the weekly dummies for all deaths occurring between 1979 and 1998, with the reference period being *Week(−1)*. The results for this limited sample are virtually identical to those for the full sample reported in the first row of the table.

FIGURE 2.—RELATIVE DAILY MORTALITY RISK (95% CONFIDENCE INTERVALS), WITH AND WITHOUT MENTION OF SUBSTANCE ABUSE, MCOD DATA, 1978–1988, ALL AGES



The results for substance-abuse and nonsubstance-abuse-related deaths appear in the third and fourth rows of table 2. Substance abuse deaths are 3.0% higher in the first week of the month compared to the previous week, while for non-substance-abuse-related deaths, this number is 0.77%. Notice, however, that there is an average of only 257 substance abuse deaths per day, so a 3% increase means 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 sub-

[9] They use the following ICD-9 codes: 291 (drug psychoses), 292 (alcohol psychoses), 303 (drug dependence), 304 (alcohol dependence), 305.0 and 305.2–305.9 (nondependent abuse of drugs except tobacco), 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), 947.3 and E977.3 (alcohol-use deterrents), and 980 (toxic effect of alcohol).

[10] A complete list of these codes is provided in an appendix that is available from the authors.

TABLE 3.—OLS ESTIMATES OF LN(DAILY MORTALITY COUNTS) MODEL BY DEMOGRAPHIC SUBGROUPS, MCOD DATA, 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)	
Nonmetropolitan county	1,609	0.0037	0.0088	0.0083	0.8402
		(0.0012)	(0.0012)	(0.0012)	

The reference period is *Week(−1)*. All have 11,088 observations, except for the groups defined by marital status. This information was not included in MCOD data before 1979; these models have 9,408 observations. Numbers in parentheses are standard errors that allow for arbitrary correlation in errors within each unique synthetic 28-day month. Other covariates include synthetic month and year effects plus dummies for special days of the year (for example, New Year's Day, Christmas). A complete list of days is included in note 7.

stance abuse deaths are more cyclical than other causes, they account for only 15% of the within-month mortality cycle.

C. *Heterogeneity across Demographic Groups*

Exploiting the information about decedents in the MCOD data, we can show that the within-month mortality cycle is present for a wide variety of demographic subgroups. In the first row of table 3, we report the *Week(−2)*, *Week(1)*, and *Week(2)* coefficients for the full sample from table 2. In the remaining rows of the table, we estimate separate models for subgroups based on sex (male, female), race (white, black, other race), marital status (single, married, widowed, divorced), and age (under 18 years, 18 to 39 years, 40 to 64 years, over 65 years).[11]

The results indicate the breadth of the phenomenon: in all groups, deaths are at least 0.5% higher in the first week of the month compared to the previous week, and these coefficients are statistically significant at conventional levels. The size of the cycle is large for some groups. The coefficient on *Week(1)* for males is 37% larger than for females (although we cannot reject the null hypothesis that the coefficients are the same). Compared to whites, the *Week(1)* coefficients for blacks is 4.0 times larger, and for Hispanics it is 3.0 times larger. The effect for divorced people is 3.5 times larger than the effect for married people, while for younger people aged 18 to 39, it is nearly 4.0 times larger than for people over 65 years old.

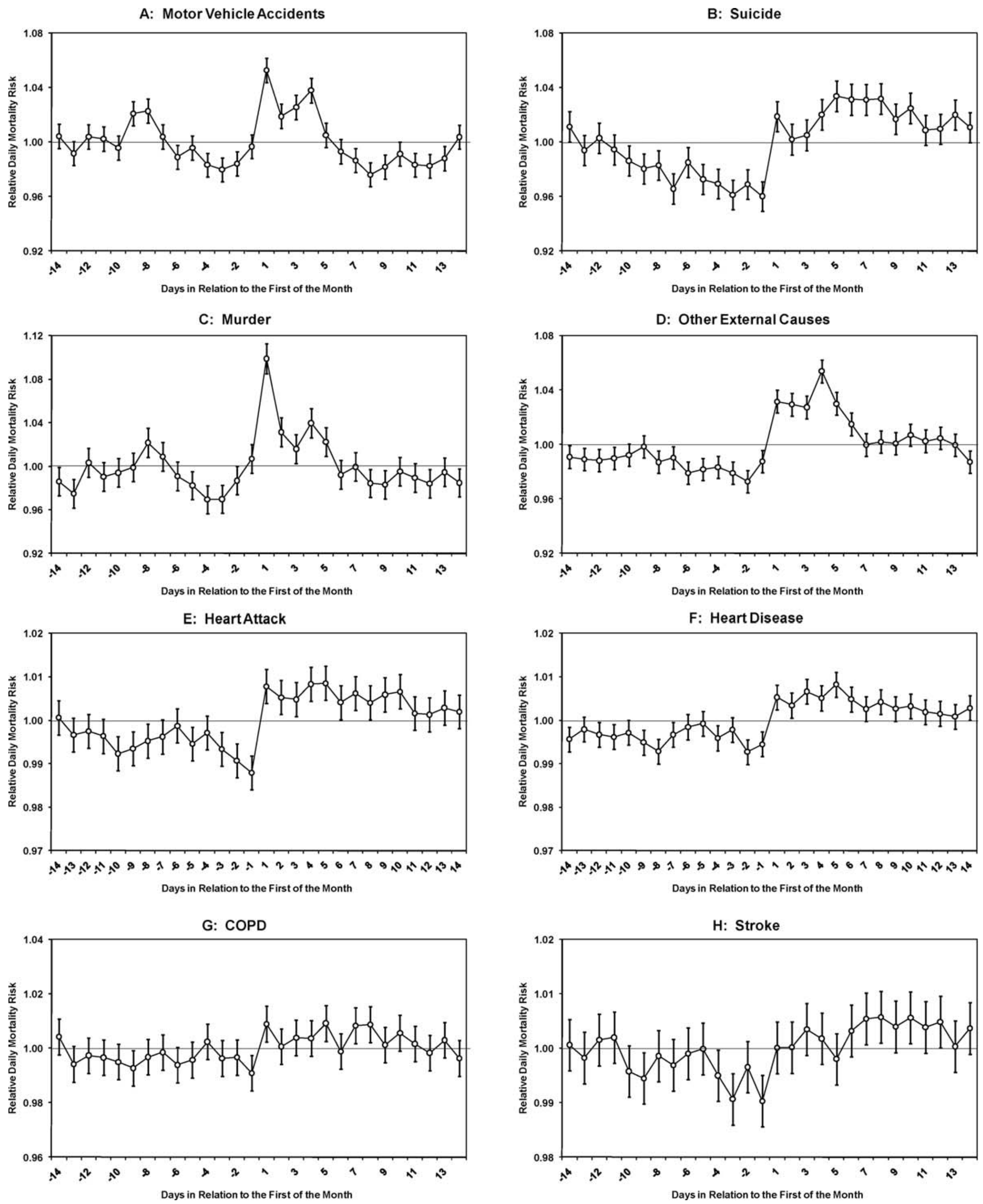
The results suggest a few things about the within-month mortality cycle. First, the persistence of the effect across all demographic groups suggests that the explanation for the within-month cycle must extend past those on transfer programs, as suggested by Phillips et al. (1999). Second, groups that generally have lower incomes and a greater propensity for liquidity issues have larger within-month cycles, with the larger cycle for males than females the only anomaly in this pattern. We show in the next section, however, that the within-month cycle is particularly pronounced for external causes and heart attacks, and it may be that the differences in results across genders result from these causes having a higher incidence rate among males.

D. *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. We create fifteen subgroups based on primary cause of death that are consistently defined across ICD-8, ICD-9,

[11] In a later section of the paper, we generate results by education level.

Figure 3.—Relative Daily Mortality Risk (95% Confidence Intervals), by Specific Causes, 1973–2005 MCOD

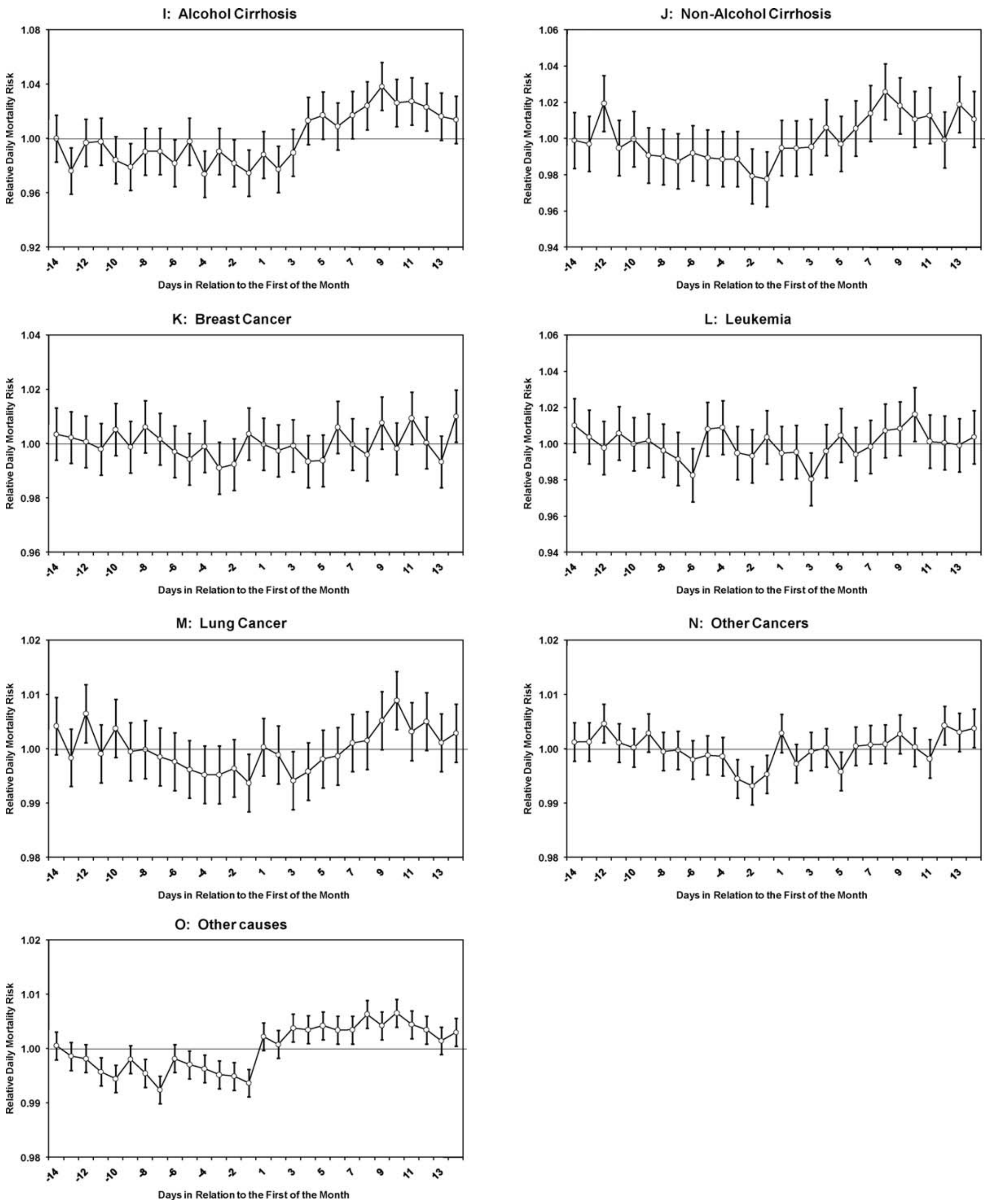


and ICD-10.[12] Four groups are based on external causes (motor vehicle accidents, suicide, homicide, and other external causes), and four are cancer-related groups (breast cancer, leukemia, lung cancer, and other cancers). The remaining categories are heart attacks, heart diseases other than heart attack, chronic pulmonary obstructive disease (COPD), stroke, alcohol-related cirrhosis, cirrhosis not related to alcohol, and a category composed of deaths not included in the previous groups.

The monthly patterns for all of these categories are shown in figure 3. Panels A to D include the relative daily mortality rates for the four external cause categories: motor vehicle accidents, suicides, murders, and other external

[12] Each ICD version has several thousand individual codes, but the changes from version to version mean that only large death categories can be consistently defined throughout the sample. The exact mapping of deaths is provided in an appendix that is available from the authors.

FIGURE 3.—CONTINUED



causes (such as accidents and drowning). All have a dip before the first of the month and a spike on the first. Deaths increase on the first by 6 percentage points for motor vehicle accidents and suicide, 9 percentage points for murder, and 4 percentage points for other external causes.

External cause-of-death categories are clearly connected to the role of substance abuse. More interesting is that the within-month mortality cycle is present in a number of the other cause-of-death categories. Panel E shows the pattern for deaths in which the primary cause was a heart attack. These deaths increase by more than 2% from the last day of the month to the first of the month. Other heart diseases, shown in panel F, display a similar pattern, although the peak-to-trough is of a slightly smaller magnitude—around 1%. The same pattern is observed for COPD (panel G) and stroke (panel H), with average differences between deaths on

TABLE 4.—OLS ESTIMATES OF LN(DAILY MORTALITY COUNTS) MODEL, MCOD DATA, 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)	
Murders	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 attack	678.0	0.19%	0.0031	0.0104	0.0067	0.956
			(0.0016)	(0.0016)	(0.0018)	
Heart disease	1268.6	0.52%	0.0013	0.0087	0.0060	0.866
			(0.0016)	(0.0014)	(0.0017)	
Chronic obstructive pulmonary disease	231.8	0.44%	0.0020	0.0055	0.0033	0.937
			(0.0028)	(0.0026)	(0.0032)	
Stroke	445.0	0.37%	0.0039	0.0050	0.0062	0.832
			(0.0017)	(0.0017)	(0.0020)	
Cirrhosis, alcohol related	33.3	100%	0.0076	0.0189	0.0387	0.128
			(0.0051)	(0.0052)	(0.0052)	
Cirrhosis, nonalcohol related	42.3	0.42%	0.0135	0.0168	0.0269	0.418
			(0.0048)	(0.0049)	(0.0046)	
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)	
Lung cancer	353.9	0.12%	0.0036	0.0022	0.0075	0.938
			(0.0019)	(0.0018)	(0.0018)	
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)	

The reference period is *Week(−1)*. All models have 11,088 observations. Numbers in parentheses are standard errors that allow for arbitrary correlation errors within each unique synthetic 28-day month. Other covariates include synthetic month and year effects, plus dummies for special days of the year (for example, New Year's Day, Christmas). A complete list of days is included in note 7. The percentage of substance abuse deaths is calculated using deaths between 1979 and 1998.

the last day of the month and the first of 1.8% for COPD and 1.0% for stroke. In all cases, the 95% confidence intervals are below the daily average in the last few days of the month and above the average in the first few days of the month.

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, peaking at 4% above the average on the ninth of the month. Nonalcohol cirrhosis deaths (panel J) exhibit a similar pattern, increasing above the average on the fourth of the month and then peaking about 3% above the average on the eighth of the month. As short-term changes in cirrhosis are influenced by changes in liver toxicity, which occurs with a lag (Cook & Tauchen, 1982), the results are consistent with higher consumption early in the month.

Finally, panels K to N contain deaths for different types of cancers. Breast cancer (panel K) and leukemia (panel L) deaths exhibit no discernible pattern. 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). Unclassified deaths (panel O) show the same pattern as aggregate mortality.

The regression-adjusted pattern for these specific causes of death is investigated using equation (1). 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 lung cancer, breast cancer, and leukemia. We find a small within-month cycle for other cancers. The largest within-month cycles are (in descending order) suicides, homicides, COPD, alcohol cirrhosis, nonalcohol cirrhosis, and motor vehicle accidents. The percentages of deaths in each category that are defined as related to substance abuse are shown in table 4: heart attacks, heart disease, stroke, COPD, and nonalcohol cirrhosis display within-month cycles, yet few deaths in these categories are connected to substance abuse.

The existence of a within-month cycle across many conditions provides further evidence of a phenomenon that requires a more general reason than alcohol and drug use. The absence of the relationship in leukemia, breast cancer, and lung cancer deaths also limits the possibility that the cycle is due to the way in which death records are kept. Given that many types of cancer are generally found to be unrelated to socioeconomic status (Phelan et al., 2004; Espinosa & Evans, 2008), this also increases the possibility that income and economic activity play some role in the phenomenon.

TABLE 5.—OLS ESTIMATES OF THE WITHIN-MONTH PURCHASE CYCLE, VARIOUS SOURCES

Outcome	Time Period	Number of Observations	Mean Daily Counts	*Week(−2)*	*Week(1)*	*Week(2)*	R^2
Ticket sales, MD pick 3 and pick 4	1/1/2003–12/31/2006	1,344	0.81 million	0.0065	0.0705	0.0319	0.924
				(0.0055)	(0.0047)	(0.0041)	
Ticket sales, OH daily number + pick 4	6/20/2005–6/16/2007	573	1.76 million	0.0121	0.0875	0.0388	0.840
				(0.0071)	(0.0061)	(0.0061)	
Visits to malls	1/1/2000–12/22/2007	2,657	25.4 million	0.0375	0.0207	0.0314	0.895
				(0.0087)	(0.0079)	(0.0079)	
Visits to retail establishments	1/4/2004–12/22/2007	1,328	94.1 million	0.0549	0.0341	0.0198	0.851
				(0.0175)	(0.0140)	(0.0145)	
Visits to apparel retailers	1/4/2004–12/22/2007	1,325	60.4 million	0.0578	0.0328	0.0225	0.850
				(0.0175)	(0.0148)	(0.0152)	
Ticket sales top ten grossing movies	1/1/1998–6/7/2007	3,171	19.3 million	-0.0100	0.0558	-0.0057	0.928
				(0.0191)	(0.0192)	(0.0237)	
Attendance at baseball games	1973–1998, 2000–2004	54,939	24,238	0.0036	0.0013	0.0337	0.872
				(0.0049)	(0.0052)	(0.0059)	
DC Metro ridership	1/1/1997–9/19/2007	3,573	494,011	0.0015	0.0035	0.0078	0.945
				(0.0070)	(0.0062)	(0.0056)	

Numbers in parentheses are standard errors that allow for arbitrary correlation in errors within each unique synthetic 28-day month. All dependent variables are natural logs. Other covariates include synthetic month and year effects plus dummies for special days of the year (for example, New Year's Day, Christmas). A complete list of days is included in note 7. Please see the text for other characteristics of specific models.

III. Linking Mortality to Economic Activity

We require a more general explanation of the within-month mortality cycle than changing levels of substance abuse. The causes of death that demonstrate the most cyclicality suggest that economic activity spurs on mortality, which means a drop in activity before the first of the month and the rise in activity after the first can explain the basic pattern of results.

While the link between economic activity and mortality is obvious for traffic accidents and other external causes that occur outside the home, extensive empirical evidence suggests that an increase in activity temporarily raises the risks of other causes of death. Nowhere is this more evident than in the literature on the triggers for heart attacks. Strenuous exercise (Mittleman et al., 1993), sexual activity (Moller et al., 2001), eating a heavy meal (Lipovetsky et al., 2004), the Christmas season (Phillips et al., 2004), and shoveling snow (Heppell, Hawley, & Channer, 1991) are all found to increase the incidence of heart attacks or deaths from heart attacks.

Given the structure of the MCOD data, we are unable to directly link increased economic activity to mortality. We can show, however, that there is a within-month consumption cycle for some specific activities and purchases. In each case, we have data aggregated to the daily level, and as a result, we use models similar to those estimated for equation (1).

The first product we consider is the purchase of lottery tickets. Most states run lotteries with daily number games, where contestants pay $1 to pick a three- or four-digit number and win $500 or $5,000, respectively, if their number is selected. We were able to obtain data on the 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 card issuers prohibit the purchase of tickets by credit cards. In some states, including Maryland, retailers are prohibited from accepting credit card payments for lottery ticket purchases. 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 and Ohio have twice-daily Pick 3 and Pick 4 games, although Ohio has no drawings on Sunday and Maryland had only a single Sunday drawing prior to May 23, 2004. We obtained daily ticket sales for the Pick 3 and Pick 4 games in Maryland from January 1, 2003, to the end of 2006 and for Ohio from June 20, 2005, through June 16, 2007.

The dependent variable is the natural log of daily sales, and we control for the same covariates as those in equation (1). In models with the Maryland data, we include a dummy that equals 1 for Sundays starting on May 23, 2004, to account for the extra draw on those days. We allow for arbitrary correlation in the errors within each unique 28-day synthetic month.

The results from these models are reported in the first two rows of table 5. Both the Maryland and Ohio lotteries have a pronounced within-month purchase cycle: ticket purchases in the first week of the month are 7.1% and 8.8% higher compared to the previous week, respectively. Both of these results are statistically significant at conventional levels.

A nationwide consulting firm for the retail trade sector that conducts a large daily survey of retail establishments and malls provided us with data on average daily foot traffic through malls (from December 1, 2000, to December 22, 2007), all retail establishments (from January 4, 2004, to December 22, 2007), and apparel establishments (January 4, 2000, to December 22, 2007).[13] The outcome of interest is the natural log of foot traffic through the establishments.

[13] As per our user agreement, we do identify the producers of the data.

The model for these outcomes is the same as above, except that we omit Christmas Day because traffic on that day is substantially smaller than during the rest of the year. The results are also reported in table 5. For malls, all retail outlets, and apparel stores, foot traffic is estimated to be, respectively, 2.1%, 3.4%, and 3.3% higher during the first week of the month compared to the previous week. These data show a pronounced within-month cycle.

We obtained data on daily box office receipts for the top ten grossing movies from www.boxofficemojo.com for January 1, 1998, to June 7, 2007. With these data, we use the natural log of the box office receipts as the outcome of interest and use the same covariates as in the previous model, with one exception. New movies are usually released on Fridays, and the top movies can change dramatically from week to week, so we define a week as a Friday to a Thursday and add a dummy variable for each unique week in the data.[14] The results for movies are reported in the sixth row of table 5, and we see that the first week of the month generates 5.6% more in revenues than the previous week.[15]

We did not find a within-month cycle for two activities for which we obtained daily data. First, we used data on daily attendance at major league baseball games for the 1973–1998 and 2000–2004 seasons from www.retrosheet.org/schedule/index.html.[16] 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 of the season, a dummy for whether it was before Memorial Day or after Labor Day, indicators for double headers, dummies for whether it was a day or night game interacted with weekday dummies, plus dummies for the team pair at a given stadium in a year.[17] We find no within-month cycle in baseball attendance.

Second, we obtained Washington, DC, Metro subway ridership figures from January 1, 1997, to September 19, 2007. The outcome of interest is log ridership, and the extra controls are dummies for Redskin home games, days during the Cherry Blossom festival, and five dummies for exceptionally large crowds on the mall, such as for the Million Man March. The results for this model, presented in the last row of table 5, show no within-month cycle.

These results are consistent with tests of the life cycle–permanent income hypothesis that have found predictable changes in income do affect consumption. Stephens (2003) found an increase in the consumption of time-sensitive purchases, like perishable food and eating at restaurants, among seniors after the receipt of Social Security checks. Using data for the United Kingdom, Stephens (2006) found an increase in consumption after the receipt of paychecks. Among food stamp recipients, Shapiro (2005) found a drop in daily caloric consumption of 10% to 15% over the food stamp month, a result he finds consistent with hyperbolic discounting. Likewise, Mastrobuoni and Weinberg (2009) found food consumption declines between Social Security payments among seniors with a high fraction of income coming from Social Security, while Hastings and Washington (2010) use store scanner data and found grocery purchases increase at the start of the month even though prices are slightly higher then.

IV. Is Liquidity Responsible for These Within-Month Cycles?

The previous two sections show there are within-month mortality and economic activity cycles that are similar in nature. There is suggestive evidence that these cycles may be due to liquidity, such as the fact that the mortality cycle is greatest for groups we would expect to have more liquidity issues (younger people, minorities, divorcees). The most striking evidence is that the one good that must be purchased with cash, lottery tickets, shows the largest peak to trough at the first of the month. In this section, we provide three pieces of further evidence that liquidity problems at the end of the month are responsible for the within-month cycles.

First, we use data from the Consumer Expenditure Survey to show there is a within-month cycle in individual purchasing behavior and that this cycle is more pronounced for groups we anticipate have greater liquidity issues at the end of the month. Next, we demonstrate that the within-month mortality cycle is largest for those with the lowest education levels. Finally, we provide evidence that the receipt of income leads to a short-run increase in mortality.

A. *Heterogeneity in the Within-Month Consumption Cycle: Evidence from the Consumer Expenditure Survey*

We further examine consumption activity using data from the Diary Survey component of the Consumer Expenditure Survey (CEX), in which purchases of frequently purchased items (food, personal care items, and gasoline) are recorded. The CEX is produced by the Bureau of Labor Statistics. The sampled unit for the Diary Survey is a consumer unit (CU), which is a household containing related family members. Beginning at different points in the month, each CU provides detailed information about purchases for a fourteen-day period.

[14] Movie release dates are based on holidays and seasons; they do not seem to consistently occur at the start or end of the month (Einav, 2007).

[15] The difference between unadjusted (that is, raw data) and regression-adjusted results is largest for this outcome. The single biggest moviegoing week of the year is Christmas Eve to New Year's Eve. Over this period, the average daily gross of the top ten movies is more than twice the average during the rest of the year. Therefore, a plot of average daily gross by days in relation to the first of the month would show a tremendous spike in attendance before the first of the month. However, adding the list of special days to the regression controls for the Christmas effect on movie attendance.

[16] There were no attendance data for the 1999 season on the Web site.

[17] For example, there was a single dummy variable for all of the Red Sox–Yankees games played at Fenway Park in 1990.

TABLE 6.—OLS ESTIMATES OF DAILY CONSUMPTION EQUATIONS, 1996–2004 CONSUMER EXPENDITURE SURVEY DIARY DATA FILE

	Week (−2)	*Week* (1)	*Week* (2)	Mean ($)	*Week* (−2)	*Week* (1)	*Week* (2)	Mean ($)	*Week* (−2)	*Week* (1)	*Week* (2)	Mean ($)
	All families ($N = 715{,}213$)				Family Income Below $30,000 ($N = 338{,}890$)				Family Income or Above $30,000 ($N = 182{,}263$)			
Food	−0.059	0.272	0.183	15.38	0.020	0.561	0.172	12.65	−0.572	−0.508	0.174	22.46
	(0.107)	(0.108)	(0.119)		(0.130)	(0.135)	(0.145)		(0.263)	(0.255)	(0.286)	
Nonfood	0.017	0.159	0.213	12.58	0.036	0.229	0.128	10.00	−0.493	0.032	0.100	20.01
	(0.134)	(0.136)	(0.147)		(0.161)	(0.159)	(0.172)		(0.348)	(0.360)	(0.383)	
Total	−0.062	0.421	0.383	27.86	0.023	0.780	0.271	22.61	−1.086	−0.480	−0.031	42.30
	(0.193)	(0.197)	(0.220)		(0.238)	(0.237)	(0.261)		(0.492)	(0.494)	(0.552)	
	Head Has Less Than High School Education ($N = 109{,}069$)				Head Completed High School but Not College ($N = 349{,}915$)				Head Completed College ($N = 256{,}229$)			
Food	−0.119	0.975	0.268	12.37	0.131	0.470	0.274	14.47	−0.273	−0.278	0.025	17.91
	(0.253)	(0.253)	(0.278)		(0.145)	(0.148)	(0.161)		(0.196)	(0.197)	(0.218)	
Nonfood	0.040	0.018	0.018	8.39	0.003	0.252	0.231	11.76	0.009	0.095	0.237	15.59
	(0.278)	(0.262)	(0.297)		(0.177)	(0.182)	(0.196)		(0.259)	(0.262)	(0.281)	
Total	−0.119	0.957	0.237	20.67	0.107	0.725	0.487	26.16	−0.266	−0.202	0.276	33.26
	(0.446)	(0.419)	(0.482)		(0.260)	(0.266)	(0.294)		(0.371)	(0.370)	(0.414)	
	Household Has Government Income Assistance Other Than Social Security ($N = 34{,}372$)				Household Has Social Security but No Other Government Income Assistance ($N = 130{,}239$)				Household Has No Government Income Assistance ($N = 550{,}602$)			
Food	−0.227	2.868	1.173	13.49	0.206	0.732	0.259	13.14	−0.102	0.005	0.110	16.03
	(0.454)	(0.497)	(0.518)		(0.208)	(0.219)	(0.237)		(0.126)	(0.126)	(0.140)	
Nonfood	−0.082	0.600	−0.564	9.29	−0.055	0.539	0.330	9.44	0.048	0.047	0.244	13.54
	(0.528)	(0.539)	(0.562)		(0.247)	(0.251)	(0.278)		(0.160)	(0.162)	(0.174)	
Total	−0.326	3.479	0.570	22.75	0.160	1.228	0.601	22.54	−0.083	0.037	0.338	29.45
	(0.819)	(0.850)	(0.910)		(0.364)	(0.377)	(0.424)		(0.233)	(0.233)	(0.260)	

The reference period is *Week(−1)*. Standard errors are in parentheses and allow for within-person correlation in errors. Covariates include a complete set of dummy variables for age, sex, race, and education of reference person; region; urban area; family income; weekday; month; year; and special days during the year, which are listed in note 7. Numbers are in real December 2008 dollars.

We use three CEX data files containing information on people who began their two-week diaries from 1996 to 2004. The first is the Consumer Unit Characteristics and Income File, which contains data about the household and its head. The second is the Member Characteristics Income File, which records the income of each CU member. The third is the Detailed Expenditure File. This lists each item's purchase date, price, and Universal Classification Code, which enables items to be grouped into detailed product categories. We have data from 57,972 CUs and roughly 715,000 daily observations, or about 12 daily observations per CU.

We create three daily expenditure categories for each household: all food purchases, including fast food and restaurant purchases; nonfood items, which consists of alcohol, cigarettes, apparel, gasoline, entertainment, personal products, personal services, and over-the-counter drugs; and sum of these two categories. We create the same synthetic month categories as before (December 18 through January 14 is *Month 1*, and so on), and convert all expenditures into real December 2008 values.[18]

The dependent variable is real daily expenditure in dollars for the household, and the regressions are similar to those using equation (1). Additional covariates include complete sets of dummies for each household head's age, sex, race, marital status, and education. We also include a complete set of controls for the region of residence, size of the urban area, family size, and reported income. The key explanatory variables are *Week(−2)*, *Week(1)*, and *Week(2)*, with the week prior to the first of the month serving as the reference period.

In the first panel of table 6, we report regression estimates for all the CUs in our sample. All three purchase categories have the familiar within-month cycle. Food purchases during the first week of the month are 27 cents higher than the preceding week, an amount that is 1.8% of the sample mean. Nonfood items show a statistically insignificant increase of 16 cents a month. The purchase of all items is 42 cents higher (1.5% of the sample mean) in the first week of the month than in the previous week. The magnitudes of these results are similar to the size of the peak-to-trough in the within-month mortality cycle.

The start of the month is a focal point of economic activities for many households. In the 1996–2004 CEX sample, about 10% of respondents who receive a paycheck do so monthly, and we suspect a large fraction of these people are paid on or near the first of the month. Furthermore, most federal transfer programs distributed checks on or near the first of the month. Social Security recipients who began claiming benefits prior to April 1997 receive checks on the third of each month, while Supplemental Security Income benefits are paid on the first of the month.[19] In an e-mail

[18] For synthetic *Month 1*, we use the January CPI, for synthetic *Month 2* (January 18–February 14), we use the February CPI, and so on. This approach avoids creating CPI-induced jumps on the first of the calendar month.

[19] Or on the closest prior business day if the usual payment date is a Saturday, Sunday, or public holiday.

survey of state Temporary Assistance for Needy Family programs, we found that 30 of 41 states that responded distribute checks during the first week of the month.

Likewise, many families have periodic bills that are due on or near the first of the month. In our CEX samples, half of all households that made a mortgage or rent payment during their fourteen-day survey period did so between the day before the first of the month and the first week of the month, with 14% paying on the first 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 limit their spending until these bills are paid.

In the rest of the panels in table 6, we provide more evidence that liquidity issues affect these within-month cycles by showing that the groups we would expect to have liquidity issues are precisely those with the greatest within-month cycle in the purchases they make.

First, we create subsamples based on household income by dividing the CEX sample into households with annual incomes of less than $30,000 and households with incomes of $30,000 and more.[20] Results for these two groups are reported in the second and third panels in the first row of table 6. Among low-income households, we find a statistically significant coefficient on the *Week(1)* dummy for the food and total spending categories. In the total purchases model, for example, the coefficient of 78 cents is about 4% of the sample mean. Among families with an income of $30,000 or more, we actually find a negative and statistically significant coefficient on the *Week(1)* dummy variable for food purchases.

Next, we divided the sample into three groups based on the household head's education: those with less than a high school education, those with a high school education or some college, and those with a college degree or more. The results are presented in the second row of table 6. In the least-educated households, food expenditure increases considerably after the first of the month: the *Week(1)* coefficient is a statistically significant 98 cents, or 8% of the sample mean. These households' expenditure on all items in *Week(1)* is also positive and statistically significant. Among CUs with a high school–educated head, there are statistically significant within-month purchase cycles in the food and all items categories. In the all items category, the coefficient on the *Week(1)* dummy is $0.73, or about 2.8% of the sample mean for daily spending. Finally, for the most educated group, we find no evidence of a within-month cycle for any spending category and, like the highest-income group, statistically insignificant negative *Week(1)* coefficients for food purchases and all purchases.

[20] There is a third income group: those not reporting income. We have 194,060 observations for this group. Their results look similar to the results for low-income families, which is not surprising, as the average education of the reference person in these households is close to the education of the reference person in the low-income group.

In the final group of results, presented in the final row of table 6, we group households based on their receipt of government income. The first group consists of households with any federal or state income assistance other than Social Security. Most of these families received income from either the Temporary Assistance for Needy Families (TANF) or the Supplemental Security Income (SSI) programs. There is a large within-month cycle for this group, with food purchases $2.87 higher (21% of the sample mean) and total purchases $3.48 (15% of the sample mean) during the first week of the month compared to the previous week. The *Week(1)* coefficient on nonfood consumption is also positive but not statistically significant.

The second group consists of households receiving Social Security but no other government income. This group is similar to the sample used in Stephens (2003), although all in his 1986–1996 sample are paid on the third of the month, while our 1996–2004 sample contains some Social Security recipients being paid at other times of the month.[21] As the results in table 6 indicate, we find positive and statistically significant *Week(1)* coefficients for these households' purchases of food items (73 cents), nonfood items (54 cents), and all items (123 cents), which represent about 5% of the daily mean in each category.

The third group in this block of results is a sample of households with neither Social Security income nor income from other federal or state transfer programs. This set of estimates provides no evidence of a within-month purchase cycle.

These results suggest that liquidity drives the consumption cycle. Households receiving government transfers or with low income or education display such a cycle, while high-income and educated households do not. The results may be consistent with a hyperbolic discounting, as Shapiro (2005) and Mastrobuoni and Weinberg (2009) suggested.

B. *Mortality Results by Education Levels*

In this section, we examine the heterogeneity in the within-month mortality cycle based on the education of the deceased. Since 1989, the MCOD file has included the decedent's education, which is usually provided by the next of kin.[22] Educational attainment is strongly and positively correlated with households' wealth and financial savings (Juster, Smith, & Stafford, 1999), so education should provide a proxy for those with and without liquidity constraints.

[21] Those claiming Social Security prior to May 1997 are paid on the third of the month, while newer beneficiaries are paid on the second, third, or fourth Wednesday of the month depending, respectively, on whether the birth date is on the 1st to 10th, 11th to 20th, or 21st to 31st. http://www.socialsecurity.gov/pubs/calendar.htm.

[22] In 1989, 21 states reported education for at least 90% of decedents. This number rises to 42 states by 1995 and 48 states by 2005. Sorlie and Johnson (1996) assessed the accuracy of education listed on death certificates and found that certificates match survey data obtained prior to death in about 70% of cases. When they differ, the death certificate generally overstates reported education.

TABLE 7.—OLS ESTIMATES OF LN(DAILY MORTALITY COUNTS) MODEL, MCOD DATA, 1989–2005

Group	Mean Daily Deaths	*Week(−2)*	*Week(1)*	*Week(2)*	R^2
All deaths	6,360	0.0015	0.0091	0.0074	0.934
		(0.0015)	(0.0015)	(0.0015)	
By level of education					
Less than high school	1,916	0.0021	0.0102	0.0093	0.798
		(0.0018)	(0.0018)	(0.0018)	
High school	2,908	0.0008	0.0093	0.0072	0.961
		(0.0015)	(0.0019)	(0.0015)	
College degree	664	0.0031	0.0045	0.0023	0.942
		(0.0020)	(0.0020)	(0.0021)	

The reference period is *Week(−1)*. All models have 5,712 observations. Numbers in parentheses are standard errors that allow for arbitrary correlation in errors within each unique synthetic 28-day month. 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 note 7.

We group decedents into three categories: those whose highest education is less than high school completion, those who completed high school but not college, and those who completed college.[23] The results from regressions with week-of-month dummies for these three education-based groups are shown in table 7. The within-month cycle is present for all three education groups. With *Week(−1)* again the reference week, the largest coefficient on *Week(1)* is for those who did not complete high school (1.0%), followed by high school completers (0.93%) and those with a college education (0.45%). The *Week(2)* coefficients display the same pattern: they are higher for high school noncompleters (0.93%) than high school completers (0.72%) and college-educated decedents (0.23%). This last coefficient is the only *Week(1)* or *Week(2)* coefficient that is not statistically significant at conventional levels. These mortality patterns are consistent with changing liquidity over the month, as those with less education are most likely to have liquidity problems.

The mortality results show the same general pattern as in consumer spending: that the within-month peak-to-trough decreases as educational attainment increases. A difference, however, is that we find a statistically significant first-week effect for mortality for the most educated group, while there is no discernible first-week effect in consumer spending for this group. There are large day-to-day differences in spending, both within and across households, which make type 2 errors more likely in that analysis than in the mortality models, where we have large samples and more predictable within-month differences.

C. *Income Receipt and Mortality: The 2001 Tax Stimulus Checks*

The evidence in the first two parts of this section is circumstantial with regard to our liquidity, economic activity, mortality hypothesis. We now exploit the unique characteristics of the 2001 tax stimulus checks to provide direct evidence that income receipt results in a short-term increase in mortality. We also show that this effect is primarily driven by the relaxation of liquidity and that the results are consistent with liquidity problems being most acute at the end of the month. Some of the results in this section are also reported in Evans and Moore (2011).

The Economic Growth and Tax Relief Reconciliation Act (P.L. 107-16), signed into law on June 7, 2001, was a sweeping tax bill that lowered individual and capital gains tax rates, increased the child tax credit, and made changes to estate and gift taxes. The portion of the act we consider is the reduction in the tax rate in the lowest income bracket from 15% to 10%. This tax change was applied retroactively to all income earned in 2001, and as an advance payment on the tax cuts, households with taxable income in 2000 were sent rebate checks between June and September 2001. The maximum rebates for single and married taxpayers were \$300 and \$600, respectively. Johnson et al. (2006) estimate that households received about \$500 on average, or about 1% of median annual family income. Approximately two-thirds of all households received a rebate check.

Rebate checks were mailed on ten successive Mondays, and check distribution dates were based on the second-to-last digit of the Social Security number (SSN) of the person filing taxes.[24] The first checks were sent to taxpayers whose second-to-last SSN digit was a 0 on Monday, July 23, and the last checks were sent to taxpayers whose second-to-last digit was a 9 on Monday, September 24.[25] The last three digits of the SSN are effectively randomly assigned. Johnson et al. (2006) exploit this fact using data from a special module in the CEX to show that consumption of nondurable goods increased in the months after the rebate was paid. Agarwal, Lin, and Souleles (2007) perform similar tests using administrative data on credit card charges.

We use a similar approach to examine the short-run consequences of the rebates on mortality. This is possible because the NCHS merged the second-to-last digit of a decedent's SSN from the National Death Index to the 2001 MCOD data files at our request.[26] We initially report the basic findings of Evans and Moore (2011) before showing that these rebates affect mortality in a manner consistent with the resolution of liquidity as the precipitating event.

Given that we have variation across groups in the timing of income payments from the 2001 rebates, the econometric model we use is a difference-in-differences specification. The outcome of interest is the natural log of mortality

[23] Between 1989 and 2002, the number of years of schooling rather than education outcomes is recorded in the MCOD file. Decedents were classed as having less than a high school education if 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] For married taxpayers filing jointly, the first Social Security number on the return determined the mailing date.

[25] The other checks were sent on the following dates (second-to-last digit of SSN): July 30 (1), August 6 (2), August 13 (3), August 20 (4), August 27 (5), September 3 (6), September 10 (7), and September 17 (8).

[26] The NDI is designed to assist researchers who want to ascertain whether subjects in their studies have died and includes each decedent's SSN. More information about the NDI can be found at www.cdc.gov/nchs/ndi.htm.

TABLE 8.—ESTIMATES OF LN(WEEKLY MORTALITY COUNTS) MODEL, THIRTY-WEEK PERIOD IN SUMMER AND FALL 2001, MCOD DATA

Covariates	Ages 25–64 (1)	Unmarried Males, 25–64 (2)	Ages 65 and Over (3)	Ages 25–64 (4)
Rebate	0.0269	0.0469	−0.0009	
	(0.0097)	(0.0197)	(0.0056)	
Rebate × LastWeekInMonth				0.0515
				(0.0183)
Rebate × NotLastWeekInMonth				0.0163
				(0.0119)
Percentage paying federal taxes	51.5%	75.2%	25.2%	51.5%
p-value: Group effects = 0	0.813	0.334	0.127	0.851
p-value: rows (2) = (3)				0.113
R^2	0.715	0.340	0.8411	0.718
Mean deaths per observation	1,014	304	3,285	1,014

Standard errors are in parentheses. Other covariates in the model include week fixed effects and Social Security number group fixed effects. The percentage in the sample that paid federal taxes in 2000 is estimated from the IPUMS-CPS for March 2001.

counts Y_{it}, where i indexes groups of people based on the second-to-last digit of their SSN ($i = 0$ to 9), and t indexes one of 30 seven-day periods that begin ten weeks prior to the first check being distributed and end ten weeks after the last check was sent. The estimating equation is of the form

$$\ln(Y_{it}) = \alpha + REBATE_{it}\beta_1 + \eta_i + \nu_t + \varepsilon_{it}, \tag{2}$$

where $REBATE_{it}$ is a dummy variable that equals 1 in the week that group i's rebate checks arrive. The parameter β_I therefore measures the percentage change in weekly mortality associated with rebate check receipt. The fixed-effect η_i captures persistent differences in mortality across groups; however, no such differences are expected because of the random assignation of the second-to-last digit of a SSN. The fixed effect υ_t captures differences in weekly mortality counts that are common to all groups but vary across weeks. The September 11 terrorist attacks occurred during week 18 in our analysis, and the deaths for that week are about 20% above the average.[27] The week effects will capture these changes so long as the deaths associated with September 11 are equally distributed across the ten SSN groups. The remaining variable in the model is ε_{it}, a random error term.

A key to the analysis is to reduce the sample to people with taxable income in 2000, as they were the only ones to receive a tax rebate. Estimates of taxable income are reported in the Annual Demographic file for the March Current Population Survey (CPS) data (King et al., 2004) and data from the 2001 survey (2000 tax year) suggest that 52% of people aged 25 to 64 were in households that paid federal income taxes, while the comparable number for people aged 65 and older was 26%. Therefore, we restrict our attention to people aged 25 to 64.

Even with this restriction, the sample includes many nontaxpayers. It also includes couples who filed their taxes jointly but were not listed first on the IRS 1040 form, as their household's check was mailed according to their spouse's SSN rather than their own. The IRS 1040 form does not record the sex of the taxpayers, so we cannot ascertain whether husbands or wives are more likely to be listed as the first taxpayer. As both nontaxpayers and the second person listed on joint tax returns should be randomly distributed across the different groups, our results should be systematically biased toward zero. The parameter β_1 does not measure the impact of check receipt but rather the intention to treat with a check.

The results for equation (2) are reported in the first column of table 8. There is a statistically significant 2.7% increase in mortality for adults aged 25 to 64 the week rebate checks arrive. We cannot reject the null hypothesis that the group fixed effects are all 0, which provides support for the conjecture that the latter digits of the SSN are randomly assigned. The results suggest a large short-term increase in mortality immediately after income receipt.

We use information from March CPS data to identify individuals likely to have been treated by a tax rebate. It is not clear a priori how the estimates should change. A higher fraction of taxpayers means more treated people, but it also means a larger fraction of people with higher incomes, who would be expected to have fewer liquidity problems. Single males aged 25 to 64 is a sample likely to have filed taxes in their own name, and it contains a high fraction of people who paid taxes in the previous year (in excess of 75%). The results for this "high-income, high-treatment" group are presented in column 2. There is a large and statistically significant short-run mortality effect of 4.7%. At the opposite end of the spectrum, we estimate the model using a sample of seniors aged 65 and older, a group with a low fraction of people who received a tax rebate (about one-quarter). Results for this group are reported in column 3; we find no impact of the rebate on mortality among seniors.

We postulate that a lack of liquidity at the end of the month leads to a decline in mortality, before liquidity and mortality increase on the first of the month. If so, rebate checks arriving toward the end of the month will relieve liquidity to a much greater degree than those arriving at other times and should have a commensurately greater effect on mortality.

To see if this is the case, we compare how mortality changed on the three occasions that checks arrived in the last

[27] http://www.cdc.gov/mmwr/preview/mmwrhtml/mm51SPa6.htm.

week of the calendar month to the other seven weeks in the rebate payment period.[28] In column 4 of table 8, we estimate the same model as in column 1, except that we allow the coefficient on $REBATE_{it}$ to vary based on whether the check was received during the last week of the month or at some other time. The effect of receiving a check at the end of the month is large, with mortality increasing by a statistically significant 5.2%. This is in contrast to a 1.6% increase (t-statistic of 1.37) at other times of the month. There is a p-value of 0.11 on the null hypothesis that both coefficients are equal. The results fit with our prediction that households are liquidity constrained toward the end of the month and that this constraint affects their short-term mortality risks.

The results from the 2001 tax rebate shows that the receipt of income leads to a short-term increase in mortality. In the companion paper, Evans and Moore (2011) test for this phenomenon in four other settings. The first two tests exploit the pay structure of Social Security. First, Evans and Moore follow Stephens (2003) by examining seniors who enrolled in Social Security prior to May 1997. These recipients typically received their Social Security checks on the third of the month. For this group, deaths decline just before Social Security receipt and are highest the day after payment. Second, seniors enrolling after April 1997 are paid on the second through fourth Wednesday of the month, depending on their birth date. In these younger cohorts, mortality is highest on the days checks arrive.

The third test in Evans and Moore follows Hsieh's (2003) use of Alaska Permanent Fund dividend payments. They find that in the week that direct deposits of permanent fund dividends are made, mortality among urban Alaskans increases by 13%. Finally, Evans and Moore consider active-duty military wage payments made on the first and fifteenth of the month. Among 17 to 64 year olds in counties with a large military presence, they find that mortality increases by nearly 12% the day after midmonth paychecks arrive, while over the same period, there is no change in mortality in counties with little military presence.

These five cases link short-term increases in mortality directly to the receipt of income, providing strong evidence of a connection between liquidity and mortality.

V. Explaining Mortality over the Business Cycle

A large literature has established that health outcomes are better among individuals with higher socioeconomic status (Kitigawa & Hauser, 1973). This has been documented for nearly all measures of health and health habits, including mortality (Backlund, Sorlie, & Johnson, 1999), self-reported health status (House, Kessler, & Herzog, 1990), child health (Case, Lubotsky, & Paxson, 2002), smoking (Chaloupka & Warner, 2000), and biomarkers (Seeman et al., 2008).

In contrast to this work is a group of papers that show mortality is procyclical. The basic statistical relationship has been documented for the United States (Ruhm, 2000) and several OECD countries (Gerdtham & Johannesson, 2005; Neumayer, 2004; Tapia Granados, 2005), and for many outcomes including deaths from heart disease (Ruhm, 2000), traffic fatalities (Evans & Graham, 1988), infant health (Dehejia & Lleras-Muney, 2004), and self-reported health status (Ruhm, 2003). The one death category that shows a decidedly countercyclical pattern is suicide (Ruhm, 2000; Tapia Granados, 2008).[29]

There is no definitive explanation for why mortality is procyclical. Some patterns of behavior are consistent with the opportunity cost of time increasing when an economy strengthens. For example, Ruhm (2005) finds that physical fitness declines and obesity rises in good times, while Ruhm (2007) finds there are fewer medical interventions for heart disease during booms, despite more heart disease deaths occurring during these periods. Mortality is procyclic among retirees and others outside the labor force, however, casting doubt on the extent to which this mechanism explains the phenomenon (Edwards, 2008; Miller et al., 2009).

Another possible explanation is that some consumption and economic activity, which increases over the business cycle, has harmful effects (Ruhm, 2000; Tapia Granados, 2008). This explanation involves similar linkages to the ones we have explored in this paper. If similar forces do create procyclical mortality, then the causes of death with the greatest within-month cycles should also be those most strongly tied to the business cycle.

To see if this is the case, we compare the procyclicality of mortality to the within-month cycle for the fifteen cause-of-death categories presented in table 4, using MCOD data for the 1976–2004 period. The methodology for analyzing the procyclicality of mortality dates to Evans and Graham (1988) and is typified in Ruhm (2000). When pooled time-series and cross-sectional data at the state level are used, mortality rates are regressed on state and year effects, demographic covariates, and a measure of the business cycle, which is typically the unemployment rate.

Let M_{it} be the mortality rate for state i in year t, defined as deaths per 100,000 people. The model we estimate is of the form

$$\ln(M_{it}) = X_{it}\beta + UNEMP_{it}\alpha + u_i + \nu_t + \varepsilon_{it}, \tag{3}$$

[28] These weeks begin on the following Mondays: July 23, August 27, and September 24, 2001.

[29] From an econometric standpoint, the socioeconomic status and health literature and the literature on procyclic mortality are measuring different movements in income. Typical measures of socioeconomic status include variables such as education, wealth, income, and occupational status, which 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 latter models are therefore measuring the impact of transitory changes in economic activities on mortality.

TABLE 9.—OLS ESTIMATES OF STATE-LEVEL LN(CAUSE-SPECIFIC DEATH RATE) MODEL, FIFTY STATES AND THE DISTRICT OF COLUMBIA, 1976–2004

Cause of Death	Deaths per 100,000 People	Coefficient (Standard Error) on State-Level Unemployment	R^2
All deaths	869.1	−0.0039 (0.0013)	0.968
By causes of death			
Motor vehicle accidents	21.3	−0.0319 (0.0043)	0.930
Suicides	12.9	0.0146 (0.0059)	0.886
Murders	7.9	−0.0217 (0.0080)	0.907
Other external causes	23.9	−0.0175 (0.0049)	0.803
Heart attacks	102.9	−0.0113 (0.0052)	0.963
Heart disease	177.3	−0.0014 (0.0026)	0.919
COPD	33.8	−0.0046 (0.0024)	0.963
Stroke	66.7	−0.0056 (0.0032)	0.948
Cirrhosis, alcohol related	4.9	0.0026 (0.0092)	0.826
Cirrhosis, nonalcohol related	5.9	−0.0042 (0.0079)	0.819
Breast cancer	15.6	0.0039 (0.0018)	0.910
Leukemia	7.3	−0.0000 (0.0018)	0.845
Lung cancer	50.3	0.0054 (0.0019)	0.959
Other cancers	115.4	0.0024 (0.0012)	0.968
All other causes	223.0	−0.0064 (0.0020)	0.941

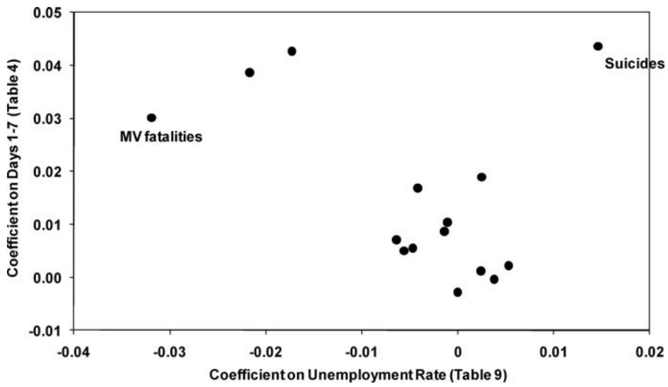
All models have data from fifty states and the District of Columbia over the 29-year period 1976–2004. The dependent variable is the log death rate (deaths per 100,000 people). All models control for state and year effects, plus the fraction black, fraction under 5 years of age, and fraction over 64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

where X_{it} is a vector of demographic characteristics, u_i and v_t are state and year effects, and ε_{it} is an idiosyncratic error term. The key covariate is the state i's unemployment rate in year t ($UNEMP_{it}$). In the model, we include in X_{it} the fraction of people who are under 18, the fraction who are 65 and over, and the fraction who are black. We allow for arbitrary correlation in the errors within a state and weight observations by population size.

Results from this regression are reported in table 9. In the first row, we report estimates for all-cause mortality. Similar to Ruhm (2000), we find a large, negative, and statistically significant impact of the unemployment rate on mortality. A 1 percentage point drop in the unemployment rate will increase mortality by about 0.4%.

In the next fifteen rows, we show estimates of the procyclicality of mortality for specific causes that are consistent with previous estimates. Traffic accidents, murders, other external causes, heart attacks, COPD, and the "all other causes" category have procyclical relationships and p-values of at least 0.1. There are statistically significant countercyclical results for suicides, lung cancers and other cancers, while diseases like breast cancers, leukemia, heart disease, and nonalcohol cirrhosis have weak relationships with the business cycle.

FIGURE 4.—SCATTER PLOT, MORTALITY AND THE BUSINESS CYCLE VERSUS THE SIZE OF THE WITHIN-MONTH MORTALITY CYCLE, BY CAUSE OF DEATH



This pattern of results is similar to the within-month pattern. To demonstrate this point, in figure 4, we plot the coefficients on the unemployment rate from table 9 along the x-axis and the within-month peak-to-trough estimates (the coefficient on the *Week(1)* dummy variable) from table 4 on the y-axis. The graph shows a pronounced negative relationship, and the correlation coefficient between the two series is −0.4. There is one obvious outlier: suicides, which have a large within-month cycle but are decidedly countercyclical.[30] When we exclude suicides from the calculation, the correlation between the coefficients on the remaining fourteen causes of death rises to −0.8. It is important to stress that we are not testing a particular hypothesis, and the results in figure 4 do not indicate a causal relationship. Rather, the strong negative correlation between the two sets of coefficients in figure 4 is meant to indicate that the most procyclical death categories are in general the same categories that exhibit the greatest within-month mortality cycle, suggesting that similar processes are driving both results.

If the within-month mortality cycle is indeed due to changes in economic activity, then the similarity in the results across death categories between this cycle and the procyclicality of mortality provides suggestive evidence that liquidity-related economic activity is the underlying cause for both. This also helps in reconciling procyclical mortality with the literature on socioeconomic status and health. Typical measures of socioeconomic status include education, wealth, income, and occupational status, which can be considered measures of permanent income. While within-month fluctuations are clearly transitory, the similarity of within-month and procyclical mortality suggests that

[30] The countercyclical pattern in suicides is concentrated among males in the working-age population (Wu & Cheng, 2010). It may be that unemployment directly heightens the risks of suicide in a way that swamps any consumption or related effects.

business cycle changes in employment and income should also be thought of as transitory at the aggregate level, despite some long-term effects at the individual level.

VI. Conclusion

When daily counts of deaths in the United States are arranged around the first day of the calendar month, what emerges is a clear pattern of deaths decreasing during the final days of the month and then spiking on the first. We show that this within-month mortality cycle is a broad-based phenomenon that is common to most subgroups and many causes of death. It cannot be satisfactorily explained by changes in drug and alcohol consumption alone.

We find that consumer purchases, mall visits, and cinema attendance exhibit similar within-month cycles. While we do not have economic activity and mortality data in a single data set, medical knowledge of the triggers for specific health conditions, combined with the similarity of the demonstrated mortality and activity patterns, suggests that short-term changes in economic activity may be the missing explanation for the within-month mortality cycle. Furthermore, these patterns are consistent with liquidity changing over the month and affecting levels of economic activity and, in turn, the number of deaths on a given day.

These results link medical literature on the within-month mortality cycle to the literature on consumption smoothing, with implications for both. For the medical literature, understanding that substance abuse is only part of the within-month mortality cycle means liquidity and payments have broader medical effects than is commonly thought. For consumption smoothing, this pattern points to the potential breadth of the excess sensitivity of consumption to the timing of payments. We use over 70 million deaths in our analysis. If the within-month cycle is mainly due to liquidity changes affecting individuals' economic activity, then excess sensitivity and its explanations, such as hyperbolic discounting, must not be limited to narrow subpopulations.

The magnitudes of the mortality patterns we describe are not small relative to other movements in aggregate mortality rates. In table 2, we estimate that mortality is 0.86% higher in the first week of the month compared to the last week. Throughout the sample period, this would have resulted in 4,324 more deaths in the first week of the month than in the last. On the basis of our business cycle calculations, this is equivalent to the additional deaths generated by a half percentage point decline in the unemployment rate.

In order to understand whether there are potential gains to smoothing liquidity, we need to know whether short-term variation in liquidity and activity is actually changing the total number of deaths or merely 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 and other external causes, it is logical that more activity leads to an increase in deaths; for conditions like heart attacks, the answer is not so clear. Analysis of one-off payments by Evans and Moore (2011) suggests that for some cases such as heart attacks, much of the variation in mortality may be harvesting, although more work needs to be done to understand this issue fully.

There are some potential policy implications suggested by our results. For example, the within-month mortality cycle and the heightened mortality associated with income receipt might suggest that emergency rooms, hospitals, police, and fire departments should adjust staffing levels in accordance with predictable high- and low-mortality days. Our search of the Internet has not yet provided any anecdotal evidence that such adjustments already exist.

Our results also suggest a complex relationship between income and mortality that may have implications for how and when people are paid. If the resolution of liquidity drives the within-month mortality cycle, then more frequent paychecks may reduce mortality. In contrast, it could be the case that having money in their pocket leads people to engage in activities that are hazardous. If this is the case, increasing the frequency of payments may make things worse. Evans and Moore (2011) provide some evidence to this point when they note that the second paycheck of the month for the military generates particularly pronounced mortality. The recent movement by some states to distribute welfare payments multiple times each month may provide a potential test for these competing hypotheses.[31]

Finally, the results have implications for our understanding of the procyclicality of mortality. The causes of death 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 are more easily separated from permanent levels of income over the course of a month than over a business cycle. The similarity of the two mortality phenomena suggests that the apparent contradiction between the protective effect of income and the procyclicality of mortality can be resolved by viewing business cycle movements as events that lead to medium-term changes in liquidity, which then affect economic activity and the mortality risks people face.

[31] Any effort to smooth mortality by increasing paycheck frequency must be weighed against the costs. Previous work on procyclical mortality suggests that the welfare benefits of such smoothing may be small (Edwards, 2009).

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