Worrying about the stock market: Evidence from hospital admissions*

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Abstract: Using individual patient records for every hospital in California from 1983-2011, we find a strong inverse link between daily stock returns and hospital admissions, particularly for psychological conditions such as anxiety, panic disorder, or major depression. The effect is nearly instantaneous for psychological conditions (within the same day), suggesting that *anticipation* over future consumption directly influences instantaneous utility.

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I. Introduction

Most papers in behavioral asset pricing explore how investor psychology influences stock prices. In this paper, we ask the opposite question. Using three decades of daily hospital admission data for the state of California, we measure the extent to which, and how quickly, stock market fluctuations impact investor psychology.

There are at least three reasons to care about the answer. First, if we think that behavioral influences are important determinants of prices, then anything that induces large, widespread changes in investor psychology is ultimately in the domain of economics.[1] Said another way, even taking as given Hamoudi and Sachs' (1999) claim that "human well-being is inarguably an end unto itself," psychological distress among investors is especially relevant for financial economists, for whom the process of price formation is of central importance.

That market movements may themselves contribute to investor sentiment introduces a second, and potentially more compelling reason: feedback. As Shiller (2002) writes, "the essence of a speculative bubble is a sort of feedback, from price increases, to increased investor enthusiasm, to increased demand, and hence further price increases (p. 22)." Yet, the majority of empirical work pertains to the first part of the feedback loop. We aim to fill this gap, and accordingly, look for a relationship between stock price fluctuations and investor psychology.

Third and finally, the speed of any effect informs us about aspects of investor preferences difficult to infer outside the laboratory. Specifically, the more quickly that

[1] There is abundant evident that events likely to impact the collective psychology of investors, but should otherwise have minimal impact on securities values, influence prices. Examples include the outcomes of sporting events (Edmans, Garcia, and Norli, 2007), sunshine exposure (Hirshliefer and Shumway, 2003), or disruptions in sleep patterns (Kamstra, Kramer, and Levi, 2000, 2003). See Baker and Wurgler (2007) for a comprehensive review of investor sentiment and the stock market.

gyrations in stock prices impact an investor's instantaneous well-being, the more likely the effect is coming through expectations over future consumption, rather than via current consumption, i.e., through the budget constraint. This distinction plays a central role in modern asset pricing theory, indeed being the defining feature of recursive preferences, but identifying an effect of expected consumption on is challenging outside the laboratory.

To address these goals, we collect data from two sources. First, we obtain admission records for every California hospital for each day from 1983 until 2011. Our proxy for the real-time psychological well-being experienced by investors is the rate at which patients from a large population are admitted to hospitals, particularly for mental health conditions such as anxiety, panic disorder, or major depression.[2] We then form portfolios of stock returns that we think are relevant for California-based investors: an index consisting of local companies. Analysis of time series regressions indicate whether, and how quickly, the stock market impacts the psychological well-being of investors.

Figure 1 provides an illustration, which plots seasonally adjusted hospital admissions for several days on either side of October 19, 1987, when the U.S. stock market fell by almost 25%. Two observations are worth noting. First, although we observe no prior trend, hospital admissions spike over 5% precisely on Black Monday. Further, there is neither a delayed effect nor a reversal, despite the fact that on October 20, about half the previous day's losses were erased. The first result indicates an immediate impact on the psychological states of investors; the second suggests an

[2] Because psychological stress can manifest other ways (e.g., stress-induced flare ups of chronic conditions not directly related to mental health), in most tests we consider a wider set of ailments.

asymmetry, whereby the utility declines following market drops outweigh any utility gains after price run-ups.

Both findings generalize over our three-decade sample. In time-series regressions, we find that on average, a one standard deviation drop in California stock prices (roughly -1.5%) increases admissions to California hospitals by 0.18% - 0.28% over the next two days, depending on the specification.[3] When we restrict our sample to health conditions that are primarily psychological in origin such as anxiety or panic attacks, we find a quicker, stronger response. Here, virtually the entire effect shows up the first day (as with the October 1987 crash), with a magnitude roughly twice that observed for non-psychological disorders. Moreover, when we break up the market return into quintiles, we find investors only respond to return shocks in the lowest quintile. There is no corresponding decrease in hospitalizations following extreme market increases.

How big is the additional health care burden caused by stock market fluctuations? This is difficult to answer precisely, given that the vast majority of stress-induced illnesses do not result in hospitalization. However, for the cases that do, we can infer the magnitude by relating hospital *charges* (rather than admissions) to stock market declines. The results of this analysis indicate at least $100 million in additional, annual hospital-related expenses for Californians, though again, the true effect is undoubtedly larger.

[3] Our regressions include fixed effects for each year, month, day of the week, and holiday period, so this relation is not driven by calendar-time effects, e.g., January simultaneously being associated with high stock returns but low rates of illness.

The relation between economic growth and health has been studied for at least four decades,[4] including recent work by Schwandt (2011), McInerney, Mellor, and Nicholas (2012), Nandi et al. (2012), Deaton (2011) and Cottia, Dunn and Tefft (2013), with causation often going in both directions.[5] Most studies have found a positive association between economic conditions and health, although see Ruhm (2000) for contrary evidence. Less clear is the mechanism: does physical well-being suffer because of reduced investments in healthy behavior (e.g., food, exercise, medication), or does the simple fact of losing money engender a negative physiological response?

The immediacy of the result – stock market declines $today$ result in psychological distress $today$ – points to the second channel, suggesting that negative shocks to expected future consumption can impact instantaneous well-being. Similar to experiencing displeasure both from a trip to the dentist's office today as well as the thought of going to the dentist tomorrow, the well-being experienced by investors appears to depend both on what he currently consumes, as well as what he may (or may not) consume in future periods. In this way, our results provide general support for the family of recursive preferences,[6] where instantaneous utility depends, in part, on the agent's expectation of future consumption.

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[4] A partial list of important contributions includes Grossman (1972), Brenner (1973, 1979), Hamermesh and Soss (1974), Brenner and Mooney (1983), Forbes and McGregor (1984), Cook and Zarkin (1986), Fogel (1994), Barro and Lee (1994), Ruhm (1995), Barro (1996), Ettner (1996), Pritchett and Summers (1996), Bloom and Sachs (1998), Strauss and Thomas (1998), Bloom and Canning (2000), Bloom, Canning, and Sevilla (2004), among many others.

[5] Another example is the result that employment status and physical health are positively correlated (e.g., Bartley, Sacker and Clarke (2001), Morris, Cook and Shaper (1994) or Mathers and Schofield (1998)). However, in many cases, it is hard to distinguish between deteriorating health being the effect rather than the cause of unemployment. This is particularly true with observations at relatively infrequent intervals.

[6] A necessarily incomplete list of papers that make use of recursive utility include Kreps and Porteus (1978), Epstein and Zin (1989, 1991), Weil (1989), Campbell (1993, 1996), Hansen and Sargent (1995), Hansen, Sargent, and Tallarini (1999), Tallarini (2000), Bansal and Yaron (2004), and Hansen, Heaton, and Li ((2005).

Of these, Caplin and Leahy's (2001) model of asset pricing with "anxious" investors is perhaps most directly related. As they discuss, the effect of anticipatory emotions is useful for explaining a number of findings, including investors' reluctance to hold stocks (e.g., the equity premium puzzle). By providing direct empirical support for the idea that price movements *per se* directly influence instantaneous well-being, our results suggest that incorporating the impact of anxiety or other anticipatory emotions into asset pricing models may be realistic.

Our final tests attempt to better understand the specific reasons why stock price movements appear to induce psychological distress. Are investors troubled by stock price declines per se, or do stock prices simply proxy for economic news that may influence job prospects, wage growth, or other non-traded types of wealth? Although difficult to completely distinguish between such portfolio and non-portfolio considerations, we gain some insight by examining whether investor reactions to market declines are concentrated among days where important economy-wide news is released.

Specifically, we read the *New York Times* (NYT) and *Wall Street Journal* (WSJ) to ascertain the reason, if any, for the roughly 1,500 worst stock market days in our sample (corresponding to the bottom quintile). Removing either geopolitical events such as wars and terrorist attacks, or macroeconomic news like changes in inflation, has no impact on our main findings.

The remainder of the paper is organized as follows. Section II describes the source of our health and stock-market data. In Section III, we present our main result that stock market fluctuations predict real-time changes in health, both mental and otherwise, and find evidence of path dependence. In Section IV, we discuss what we can learn about investor preferences from these results, and the extent to which we can identify the specific source of investor worry when stock prices drop. We conclude in Section V.

II. Measurement and data

a. Physical health and investor distress

Our tests require an empirical proxy for the real-time utility, or general well being, perceived by investors at any given point in time. Economists have long wrestled with how best to measure what is inherently a subjective quality for decades, generally resulting in two approaches. The first is to ask questions directly of subjects, such as "How happy are you with your life at the current moment?" or "On a scale from 1-10, how would you rate your stress level?"[7] The second is to observe or record behavior, and use these measurements to infer subjective wellbeing. A recent example is Krueger, Kahneman, Schkade, Schwarz, and Stone (2009), which uses time use diaries to infer the utility (or disutility) people derive from their moment to moment experiences.

We take the latter approach, using fluctuations in physical health to proxy for the collective disutility experienced by a large population of investors. This measure confers a number of advantages. First, information from hospitals is not self-reported, and is thus not subject to the usual problems of survey data.[8] Second, even with perfect survey data, physical health may provide a further window into psychological stresses experienced, but not perceived by, investors. For example, a variety of somatic conditions including asthma, back pain, and even exacerbations of multiple sclerosis

[7] See Juster and Stafford (1985) for seminal work using this methodology.

[8] Examples of such complications include: 1) respondents being sensitive to the interviewer's reaction to their answers, 2) the wording of the question creating framing or reference point effects, and 3) biased answers (e.g., when being asked about whether caring for an elderly parent is enjoyable).

have all been linked to psychological stress. Third, and finally, because our data are comprehensive, including every hospital in the state of California (see below), our estimates allow us make somewhat general, if not conservative, estimates of the overall health costs implied by stock market drops.

On the other hand, there are some offsetting disadvantages. Perhaps most important is that hospitalizations are fairly rare, occurring only in situations where acute medical attention is warranted. Because fluctuations in a person's mental or physical wellbeing (even when extreme) do not involve admission to a hospital, our estimates will underestimate the true effect. Second, our measure is implicitly asymmetric, registering only instances where people's physical or mental health experiences deterioration sufficient to justify hospital admission. Consequently, if a rising market *improves* collective mood rather than vice versa, we will capture this effect only to the extent that hospitalizations decline. Whatever the statistical power of this approach, it is clearly inferior to a measure that directly captures variation in elation or excitement, rather than simply the absence of misery.

b. Data

We collect hospital admission data directly from the state of California. In 1971, California governor Ronald Reagan signed the California Hospital Disclosure Act, which created the California Hospital Commission (Commission) and paved the way for uniform accounting and reporting by California hospitals. In June of 1982 a bill passed in the California Assembly broadened the Commission’s data collection responsibilities to include daily patient discharge data beginning January 1, 1983. An inpatient discharge record is created each time a patient is treated in a licensed hospital in

California. Licensed hospitals include general acute care, acute psychiatric, chemical dependency recovery, and psychiatric health facilities. In 1986, the Commission's functions transferred to the Office of Statewide Health Planning and Development (OSHPD) as part of the Health Data and Advisory Council Consolidation Act.

The OSHPD provided us with hospital admission data from the period January 1, 1983 to December 31, 2011. The data include patient zip code, gender, age range, date of admission, length of stay, primary and secondary diagnoses and primary and secondary treatments. Diagnoses are classified by the International Classification of Diseases version 9, or ICD-9 for short. ICD-9 codes are a system of classifying ailments, akin to the Dewey Decimal System for categorizing books with specificity increasing in the number of decimal places. For example, ICD-9 codes 460-466 correspond to acute respiratory infections, code 461 corresponds to acute sinusitis and code 461.3 corresponds to sphenoidal acute sinusitis. For some of our analysis we will be concerned with codes specifically related to mental health conditions, which are in the ICD-9 range of 290 to 319. Examples include depression (296.2), panic disorder (300.01), alcohol dependence (303) and acute reaction to stress (308).

Stock price and return data are from CRSP and firm location data are from COMPUSTAT. We merge the two datasets using the now common CRSP-COMPUSTAT link file. COMPUSTAT provides the five-digit zip code of each firm's headquarters which we use to classify the firm as in or out of California.

We merge the hospital admission data onto the return data, resulting in approximately 252 observations (trading days) per year. For example, for the market return on March 11, 2010, we will assign day t hospital admissions as those which occurred on March 11, 2010. Day $t+1$ corresponds to March 12, 2010, and day $t+2$ will correspond to March 13, 2010. This means that while day *t* will always be a trading day (by construction), day *t+k*, for some integer *k*, may not be. In this case, because March 11, 2010, is a Thursday, day *t+1* does correspond to a trading day but day *t+2* does not.

Table 1 provides summary statistics from our variables of interest. During our sample, the average number of new admits to California hospitals was 11,665 per day, with a standard deviation of 877. Unsurprisingly, the vast majority of these admits are from native Californians (98%). Six percent of all hospital admissions are for reasons related to mental health, which corresponds to an average of 686 new mental patients per day. The typical hospital patient stays for 5.68 days, with a distribution that is highly skewed: the median stay is 3 but the standard deviation is 48 days, due to a handful of extremely long hospital stays.

During our time period, stocks of California-based firms had an average return of 11 basis points per day, with those outside California averaging about 9 basis points per day. California stocks were also more volatile than Non-California stocks (standard deviation of 147 basis points compared to 110 basis points), due in large part to the disproportionate number of tech startups located in California. During the median period, the standard deviation of 252 trailing daily California returns was 103 bps, but for 5% of our observations this volatility reaches as high as 289 basis points.

III. Can the stock market make you sick?

a. Empirical specification

We test for a relation between stock market performance and health by estimating the following regression for all trading days *t* between January 1983 and December 2011:

$$\log(admissions)_{t+\tau} = \alpha \cdot return_t + \beta \cdot controls_{t+\tau} + \varepsilon_{t+\tau} \qquad (1)$$

where the dependent variable is the natural logarithm of the total number of new daily $admissions$ into California hospitals, and $return$ measures stock market performance.

We are mainly interested in the coefficient α, which measures the degree to which variation in stock market performance explains hospitalizations. In our benchmark regressions, $return$ is the daily, value-weighted stock return of companies headquartered in California divided by the time-series standard deviation of $return$. We also present results with alternative specifications, such as scaling $return$ or $admission$ by its corresponding rolling standard deviation.

As for who defines the relevant patient population, there is some variation across specifications. In most cases, we aggregate across the entire state of California; however we also reexamine our results for select subsets, such as patients suffering from particular medical conditions.

The subscripts in equation (1) are worth mentioning. Recall from Section II that the vector of stock market observations, $return$, is populated only for trading days, whereas the vector of hospital $admissions$ contains observations for every day, including weekends and holidays. This distinction is irrelevant when testing for a contemporaneous relation (τ=0) between $returns$ and $admissions$, but matters when testing for either a leading or lagging relation.

Following the notation above, τ=+1, +2, or +3 correspond to a leading relation between the stock market and health variables, allowing returns up to three days ago to influence today's hospital admissions. One reason this could occur is through $delayed$

awareness; perhaps people simply don't pay close attention to day-to-day movements in stock prices, and instead become gradually aware over the course of a few days. Another possibility is *delayed reaction*, where investors are immediately aware of market conditions, but the health consequences themselves take time to manifest.[9]

Negative values for τ, on the other hand, allow us to test for a lagging relation between health outcomes and stock market performance. This can occur if shocks to health are expected to influence future productivity or demand, but are not immediately reflected in stock prices. Recognizing that we are examining hospital admissions that were (and still are) not publicly disclosed in real time, it is possible that market participants would be less than fully aware – think about the early stages of an epidemic outbreak – of health fluctuations and/or their impact on future corporate profits. Another possibility is that health conditions are simply a proxy for sentiment, and impact not through fundamentals, but instead through price pressure effects, combined with limits to arbitrage. Our tests will permit this distinction.

Finally, the vector of *controls* in equation (1) accounts for the fact that the raw, hospital admissions data we use exhibit strong temporal patterns, both within and across years. All of our main results include *year fixed effects* to account for long-run changes in health conditions, reimbursements, or other secular changes in population health. *Month fixed effects* account for seasonality; accidents, for example, are more common in the summer, whereas infections tend to cluster in cooler months. *Day of the week fixed effects* account for any intraweek variation in admissions. Finally, we

[9] A well-known example is posttraumatic stress disorder (PTSD), which can occur years or even decades after the original stressful event or psychological insult. See, for example, Tolin and Foa (2006) for a review of PTSD research.

include indicator variables for the three days surrounding each of the following *holiday* periods: New Years Day, 4th of July (Independence Day), Labor Day, Thanksgiving, and Christmas. We have no *a priori* reason to expect returns to differ systematically around holidays, and thus no reason to expect a relation with physical health. However, because we observe a marked decline in hospital admissions during holiday periods, the inclusion of these controls increases the model's overall fit, and confers an increase in statistical precision.

a. Results

In Panel A of Table 2, we present our main result, progressively adding in control variables across columns. To start, we estimate equation (1) with τ set to zero, and so ignore any lead and lag effects. The first column shows a point estimate of about -22 basis points, with a *t*-statistic of -2.8. Moving to the right, the addition of *day of the week fixed effects* (column 2) cuts the coefficient down to -17, but *month fixed effects* (column 3) appears to have minimal impact on the estimated coefficient, besides increasing its precision. Including *year effects* (column 4) matters more, cutting the coefficient to about -13 basis points, which settles to -10 basis points (t=-2.7) once we include fixed effects for *holiday* periods.

Panel B characterizes the lead-lag relation, allowing both past ($\tau>0$) and future ($\tau<0$) stock market variables to influence current ($\tau=0$) health outcomes. Comparing columns, the data reject all cases in which health outcomes lead the stock market. For all cases in which $\tau<0$, our estimates for α are both smaller in absolute value, and statistically insignificant.[10] However, this changes in the fourth and fifth columns, the

[10] Although not statistically significant, we note that the magnitude of the coefficient when $\tau=-1$ is larger than its predecessors (e.g., $\tau=-2$ or $\tau=-3$). Some of this may reflect the fact that returns are measured from close-to-close

former of which we have already seen in Panel A. Comparing these estimates, it appears that about half the effect of stock market fluctuations on health shows up the same day, with an equal effect showing up the next day. Together, a one standard deviation drop (≈-1.4%) in the stock returns of California-based companies increases daily hospital admissions by about .18%.

Table 3 presents alternative specifications. The dependent variable is now the natural log of the combined day *t* and day *t+1* admissions, as these were found to be the relevant days in event time (Table 2, Panel B). The controls are the same as in Table 2, and we calculate Newey-West standard errors with one lag, because the overlapping (2-day) dependent variable creates autocorrelation in the residuals. Thus, column 1 of Table 3 is simply an aggregation of columns 4 and 5 (days t and t+1) in Table 2, Panel B and so it is no surprise that the coefficient on *return* in column 1 of Table 3 is -9 basis points (t-stat -2.8), nearly an average of the two coefficients in columns 4 and 5 of Table 2, Panel B.

The second column of Table 3 scales return by a rolling one-year standard deviation rather than the standard deviation averaged over the entire sample. Observing that volatility varies over time, our idea is that market declines of a given size (say -3%) might elicit a more severe response, should they occur in a low-volatility regime, where return realizations this extreme are relatively unusual. Scaling returns by a dynamic average tests precisely for this, giving more weight to return realizations that occur in low volatility regimes (say, 15%) versus those occurring in more volatile times (30%).

(i.e., 1 p.m. PST to 1 p.m. PST the next day) and hospitalizations are measured from midnight to midnight (PST). There is thus the possibility for investors to react to information released after markets close (1 p.m. PST) but before midnight PST, such as earnings announcements.

In this case, the estimated coefficient increases in both magnitude and statistical significance, from about 9 basis points to over 13 (t=3.77), measured over two days. This suggests that insofar as health outcomes reflect changes in subjective well-being, the impact of a given-sized market decline is accentuated when investors are more "surprised." Although we do not present a specific model to microfound this effect, we note that this is consistent with investors evaluating either the level or volatility of future consumption with respect to a reference point, e.g., the prospect theory of Kahneman and Tversky (1979).[11]

Because hospital admissions are a persistent variable and a rolling standard deviation is also a persistent variable, the remaining columns consider the stock market predictability for *changes* in admissions rather than *levels*. Specifically, the independent variables are the same as in column 2 but the dependent variable subtracts off a rolling average of admissions. Columns 3 (4, 5, and 6) subtract off a 1-day (1-month, 6-month and 12-month) moving average of the dependent variable and the conclusions hardly change. The coefficient on *return* ranges between -11.49 basis points and -14.04 basis points and is significant in all of these alternate specifications.

One question that arises immediately from the results in Tables 2 and 3 pertains to the linearity of the specification. In particular, one might expect for extreme drops in the market to generate especially high stress levels; or, perhaps sharp market increases lead to a reduction in the baseline rates of hospitalization. To investigate these possibilities, in the first two columns of Table 4 we repeat the specification of column 2 of Table 3, but we allow for *return* to enter through a series of dummy variables, one for

[11] See also Loewenstein and Prelec (1992) and Bowman, Minehart, and Rabin (1999) for models with reference-point dependent utility specifications.

each quintile in the empirical distribution. We see that only returns in the bottom quintile impact hospital admissions. When the market is in the bottom quintile of its distribution hospitalizations increase by .31% over the next two days.

The last two columns of Table 4 allow us to estimate the hospital costs associated with these large stock market declines. We replicate the first two columns of Table 4, but we replace hospital admits with *hospital charges* as the new dependent variable. Again, we find that only the bottom quintile of returns is significant. Given that two-day hospital charges in California average \$305 x 2 = \$610 million (Table 1), and that Table 4 indicates a .37% increase in costs associated with a bottom quintile return, this implies an annual cost of \$610 million x .37% x 252 (trading days) x 1/5 = \$114 million in 2011 dollars. Extrapolating to the U.S. based on population would increase this by approximately an order of magnitude.

However, for two reasons we urge caution when attempting to infer the true economic magnitudes from these results. First, hospital care represents less than one-third of all health care costs in the U.S.[12] However, even this would be a conservative estimate of the health burden, given most stress-induced illnesses do not result in hospitalization. As a specific example, 36 million Americans suffer from migraine headaches. In 2010, the cost of inpatient hospitalizations for migraines was only \$375 million, compared to the cost of outpatient visits which totaled \$3.2 billion (Insinga, Ng-Mak, and Hanson, 2011).

[12] According to 2009 census data, approximately 31% of health care costs are hospital costs. See http://www.census.gov/compendia/statab/2012/tables/12s0134.pdf

b. Mental health conditions

To be more precise about the psychological costs imposed by stock market fluctuations, we repeat our main analysis, but consider only those ICD-9 codes labeled "Mental, Behavioral and Neurodevelopmental Disorders" by the Center for Disease Control (CDC).[13] These are ICD-9 codes in the range 290 to 319 and include depression (296.2), panic disorder (300.01), alcohol dependence (303) and acute reaction to stress (308). Broadly speaking, these are codes related to mental health.

The first four columns of Table 5 shows that the instantaneous (day *t*) relationship between stock prices and hospitalizations is stronger for conditions related to mental health. Columns 1 and 3 indicate that in the linear specification a one standard deviation drop in the stock market corresponds to a 14 bps increase in hospitalizations involving non-mental health codes, but a 21 bps increase for those related to mental health. The results are more pronounced when we examine extreme returns (columns 2 and 4). For non-mental disorders a bottom-quintile return corresponds to a 25 bps spike in hospitalizations whereas with mental disorders, the coefficient more than doubles (58 bps).

The second four columns study the one day lagged (day *t+1*) relationship. Comparing columns 5 and 6 to columns 1 and 2, we see a nearly identical set of coefficients, indicating that stock prices declines yesterday continue to increase non-mental health related hospitalizations today. In sharp contrast, the lack of significance in either columns 7 or 8 indicates that the effect of price declines on mental-health related hospitalizations is entirely concentrated in the first day (columns 3 and 4). One

[13] See ftp://ftp.cdc.gov/pub/Health_Statistics/NCHS/Publications/ICD9-CM/2011/

interpretation of this difference is that the initial manifestations of stress are mental, with more gradual effects on other organ systems as the effects accumulate.

IV. What can the health-wealth relation tell us about investor preferences?

Attempting to characterize investors' preferences has been a particularly active area in theoretical asset pricing research over the last three decades. One common approach is to posit a functional form for utility, take first order conditions, and compare the moments (e.g., stock returns or risk free rates) implied by the model to those obtained from real world data. The smaller the pricing errors associated with a particular model, the more accurately it is thought to reflect latent investor preferences.

A complementary approach, the one taken here, attempts to infer investor preferences by analyzing more direct measures of utility. Intuitively, by observing high frequency variation in psychological distress – our proxy for instantaneous well-being – it should be possible to shed light on both the timing and types of events that appear most relevant for investors. In section (a) below, we focus on timing, specifically on the distinction between the utility effects of current versus expected consumption. Section (b) discusses different types of events that may influence investor utility – e.g., whether psychological distress is more sensitive to declines in one's stock portfolio versus, say, expected wage growth.

a. Consumption versus expectation utility effects

The first distinction we make concerns how the timing of consumption impacts current utility. In the standard expected utility framework, instantaneous utility is a function only of instantaneous consumption, or

$$u_t = g_t(c_t) \tag{2}$$

where u_t and c_t are instantaneous utility and consumption respectively, and g_t is a generic utility function operating at time t. This simple formulation has two important implications. First, to the extent that u can be given a psychological interpretation, it posits that the agent's current level of well-being is defined solely by current experience, be it a fine meal or trip to the dentist's office. Second, future events can influence current utility, but only through their impact on current consumption. For example, if a young worker's employer changes its actuarial assumptions for its pension contributions, this can still impact the worker's utility, provided that he or she adjusts today's consumption in response.

It is different to claim that an agent's instantaneous utility is directly a function of consumption (or expected consumption) in future periods, i.e.,

$$u_t = f_t[g_t(c_t), E(C_{\tau>t})] \tag{3}$$

where g is the same generic function as in equation (2), and f is a function that translates concern over expected future consumption, $E(C_{\tau>t})$, to instantaneous utility. In such a "recursive" utility formulation, news of a dental cavity has two potential influences on utility – although the drilling itself is likely to be unpleasant, anticipating the discomfort compounds the effect.

The distinction between recursive and non-recursive utility formulations enjoys a long tradition in asset pricing research, beginning with Kreps and Porteus (1978), and gaining additional prominence with Mehra and Prescott's (1985) formalization of the "equity premium puzzle." In that paper, the authors show that the standard expected utility model (realistically calibrated) is incapable of explaining the high average returns of stocks, paving the way for a number of recursive models (e.g., Epstein and Zin, 1989, 1991), which have shown more promise in this regard.

One particularly relevant specification for our purposes is the model by Caplin and Leahy (2001), who incorporate explicitly into a risk-averse agent's preferences the effect of anticipatory emotions on the demand for risky assets. As they show, when investors experience nervousness or anxiety related to risky assets, the consequent reduction in current utility reduces the price they are willing to pay. This insight has implications not only for asset pricing dynamics (including the equity premium puzzle, see section IV.B), but also for information dissemination, particularly involving financial assets whose impact on current consumption may be minimal.

Yet, despite the intuitive appeal of future events influencing an agent's happiness today, empirical evidence that expectations impact current utility is scarce. The reason, in large part, is that instantaneous consumption is not observable, making it difficult to rule out the contemporaneous consumption channel (the effect of $g()$ in equation (3) above), let alone reverse causality.

A good illustration of the identification challenge is the well-documented positive relation between mental health and employment status. Numerous studies show that being employed is associated with lower rates of mental illness (e.g., Priebe et al. (2005)). However, this is consistent with three distinct channels. First, people who suffer from mental health may simply be less productive (reverse causality), or for other reasons less likely to enter the labor force. Second, employment status may change access to medical services, such as therapy or prescription medications. Last, concern over being or becoming unemployed may have a direct utility effect, leading the World Health Organization (2011) to credit the recent economic crisis with causing devastating mental health effects.

By contrast, the high frequency nature of our empirical tests makes it easier to specifically identify the effect of financial expectations on current well-being. Although hospitalizations, particularly those related to psychological distress, are undoubtedly related to the quality of medical care accessed by patients (the consumption channel), this is implausible at the daily frequency. In other words, it is difficult to imagine how changes in an agent's lifetime budget constraint could, in a matter of a few hours, translate to consumption changes (e.g., missed therapy) large enough to warrant hospital admission for, e.g., anxiety, depression, or panic disorder. Instead, the immediacy of our main result, combined with it being particularly strong for conditions related to mental health, suggests that investors care directly about their consumption opportunities in the future, beyond their impact for today's consumption.

To summarize, the results in Tables 2 through 5 suggest three aspects of investor preferences that, outside experimental settings, may be difficult to observe otherwise:

1. First, expectations *per se* about future consumption are important for current utility. This follows from instantaneous impact of stock market changes on both mental and physical health, and provides more direct

support that the standard expected utility framework is an inadequate description of investor preferences.

2. Second, the effect of expectations on current utility is asymmetric, mattering only for sharp decreases. This suggests that investors are risk averse not only with respect to current consumption (i.e. *g()* in Equation (3) is concave), but also with respect to expectations of current consumption (i.e., *f()* in Equation (3) is also concave). This is consistent with reference-point models of utility.

Of course, in any discussion like this, there are more caveats than certainties. We do not wish to imply that health outcomes encompass the entire spectrum of well being, and thus, do not claim that our results allow for a full characterization of investor preferences. Moreover, while the immediacy of our results suggest a direct role for expectations, it is possible that some of our results could result from consumption-driven changes in behavior.[14] Yet, the role that expectations seems to play for current perceptions of well-being, particularly with mental health, seems undeniable, and provides an empirical foundation for utility formulations that explicitly take this into account.

[14] It is worth noting here, however, that generally, our results go in the opposite direction from that predicted by, e.g., Ruhm (2000), which finds that recessions are generally associated with better health outcomes (with suicide being an important exception), largely through the curtailing of such risky activities such as smoking or overeating.

b. Portfolio versus non-portfolio effects

The discussion in the last section indicates that in addition to current consumption, investors think about the future, and this impacts their well-being today. However, we have not specified whether the relevant expectations pertain to stock market declines *per se,* versus the simultaneous arrival of economic news, perhaps about (potentially local) income or job growth. Through the remainder of this section, we refer to these as *portfolio* and *non-portfolio* effects, respectively.[15] In this section, we attempt to distinguish between them.

The first attempt takes a brute force approach to the problem. We start by identifying the set of 1,463 days that comprise the lowest 20% of returns over our sample period. Harkening back to Table 4, these days are almost entirely responsible for the relationship between returns and hospital admissions. The question is whether investors might be responding to news that accompany and/or cause the low average returns realized on these days, rather than the negative portfolio shock.

To assess this possibility, we collect and read the *New York Times* (NYT) and *Wall Street Journal* (WSJ) the day following each of the 1,463 returns in the bottom quintile. In each case, we determine whether a news event is identified as the reason for the decline, and if so, classify them as follows: 1) macro announcements (MA), 2) foreign conflicts or terrorist attacks (FC), 3) firm announcements (FA), 4) prices in other markets (OP) and 5) other events (OE).

[15] One might argue that this distinction is unimportant, given that it amounts to little more than capitalization – i.e., whether investors care more about losing a dollar already earned, versus one they expect to earn in present value. On the other hand, extensive experimental evidence (Kahneman, Knetsch, and Thaler (1990)) suggests an "endowment" effect that, in the current context, would seem to make losses to one's existing financial portfolio especially painful. Moreover, to the extent that we are interested in addressing the feedback loop between sentiment and securities prices, we have a special interest in how these prices, per se, influence the perceived well-being of investors.

A little more than half the time (56%), no news event is provided. Although this may seem surprising, it is consistent with Cutler, Poterba and Summers (1989) who read the New York Times in an attempt to identify the reason for the largest 50 stock price movements in their sample and find several instances in which large stock movements were unaccompanied by fundamental news. Recently, Cornell (2013) repeated the analysis of Cutler, Poterba and Summers (1989) in an updated sample, concluding that the mystery of unexplained price movements has grown: "Only a minority of the 50 largest moves in the last 25 years can be tied to fundamental economic information that could have had a pronounced impact on cash flow forecasts or discount rates. If anything, the mystery has deepened because the size of the unexplained market movements has grown." (p. 38)

Below is an example of a story classified we classified as "no news:"

"The Dow Jones Industrial Average fell nearly 46 points yesterday, the biggest one-day point loss in its history, as major investment houses, relying on computerized trading programs, sold shares heavily." (NYT, 06/09/1986)

In contrast, a story attributing returns to foreign conflict (FC):

"New threats by president Saddam Hussein of Iraq toppled stocks yesterday in the wake of new fears that war in the Persian Gulf could be nearer." (NYT 10/09/1990)

Foreign conflicts are reported in 50 cases, with macro announcements accounting for another 203 event days. Stories invoking prices in other markets (e.g., oil or foreign exchange) were observed 115 times, and those involving firm announcements were seen 241 times. We classified 148 stories in the "other event" category; these were instances where we were not comfortable classifying the story as a non-event, but could not justify any of the other categories.

In Table 6, we re-run the specification shown in Table 4 (with dummy variables for extreme returns), but exclude certain types of news stories. The first column shows the benchmark result in Table 4 for comparison. In the second column, we exclude the 50 days that involved a terrorist attack or foreign conflict. These are arguably the events most capable of independently impacting investor well-being, and in many cases, were accompanied by extreme market declines. Accordingly, if their exclusion meaningfully altered our results, a portfolio-based explanation of our main results would become suspect. As seen however, the coefficient is nearly identical to the prior column at 32 bp over two days (t=3.41), suggesting that these days play virtually no role in the main health-wealth relation.

The third column of Table 6 is perhaps the best evidence that our main result is, at least in part, a response to the stock market per se rather than the news it reflects. In it, the bottom quintile dummy turns on only for returns in the bottom quintile that are not associated with *any news event*. Examples would include "nervous investors", "program trading" or "profit taking," rather than a specific news event. As before, the coefficient of interest remains unchanged at 31.71 bp (t=2.63), indicating that the relation between hospitalizations and market downturns is nearly identical on news versus non-news days. To the extent that our classification algorithm adequately captures events capable of independently impacting investor well-being, these results in Table 6 point to a portfolio-based interpretation of the main results shown in Tables 3 and 4.

A second way to approach this issue is to exploit geographic differences across firm headquarters. Intuitively, the idea is that for California residents, stock price fluctuations of California-based firms will contain, on the margin, more non-portfolio information (e.g., about job security) than firms not headquartered in California. For example, if Google misses earnings, this may cause its stock price to drop, which will adversely influence the portfolio of any investor in Google stock, irrespective of where he/she lives. However, an investor living in California – particularly in the Bay Area – will not only be exposed to this portfolio loss, but also to other losses through, e.g., real estate prices, slowdown in labor markets, etc. Continuing this reasoning, a decline in Google combines portfolio and non-portfolio effects, whereas a non-local firm such as Dallas' ExxonMobil should influence investors primarily through its impact on their portfolios.

Table 7 shows the results of this analysis, where we compute the daily value-weighted return to all companies not located in California (*Non-California Return*). Column 1 shows the continuous return specification (similar to column 2 of Table 3), and column 2 shows the dummy specification (similar to column 1 of Table 4). When we allow continuous non-California returns by themselves to influence California hospital admissions(column 1), we find a positive and significant coefficient of -9 bps (t=2.59). This is comparable to, although somewhat smaller, the benchmark specification in Table 3. The discrete specification is in the final column and the coefficient of 35 (t=3.83) is slightly larger than the benchmark specification (31 bps) in

Table 4. We take this fact – that non-California returns put Californians in the hospital -- as circumstantial evidence of portfolio effects.

V. Conclusion

Over roughly three decades, we provide evidence that daily fluctuations in stock prices has an almost immediate impact on the physical health of investors, with sharp price declines increasing hospitalization rates over the next two days. The effect is particularly strong for conditions related to mental health such as anxiety, suggesting that concern over shocks to future, in addition to current, consumption influences an investor's instantaneous perception of well being.

That we observe such a swift health response to stock prices – in most cases within two days of a price drop – suggests two takeaways. First, from the perspective of trying to infer the types of information that investors view as most relevant for their portfolio decisions, our estimates indicate that expectations about the *future* play a direct role in determining *today's* utility. This is important because outside laboratory settings, the ability to identify the utility impact of expectations, apart from contemporaneous consumption, is usually not possible. In our case, the high frequency timing of our tests makes it so, providing empirical support for utility specifications that explicitly take into account concern for the future.

Second, given that we are observing the aggregate reactions of the public at large, it is natural to think about the welfare implications associated with the widespread dissemination of financial information, on an almost minute-to-minute basis. Indeed, as Caplin and Leahy (2001) show, when investors worry about the future, a policy of revealing *all* information as soon as it becomes available may in fact reduce welfare, particularly regarding those whose actions have little bearing on the outcome (the recent barrage of media coverage of the "Fiscal Cliff" of 2012 comes to mind). Moreover, their distress may be compounded to the extent that the media amplifies the impact of fundamentals (see, e.g., Dougal et. al (2012)). Accordingly, we view a worthy goal of future research to better characterize the independent effect of the financial media on health outcomes or other measures of investor utility.

Finally, we note that while using aggregate data is useful for providing an estimate of the aggregate effect on investor utility (particularly at the left tail), it potentially masks interesting interactions. For example, from the financial economics perspective, it would be interesting to understand whether the health responses we observe are relevant for the marginal price setter, which could potentially generate the types of feedback effects discussed by Shiller (2002). These and similar questions we leave to future work.

References

Baker, M., and Wurgler, J., 2007, Investor Sentiment in the Stock Market, *Journal of Economic Perspectives*, 21 (2), 129-151.

Barro, R., 1996, Health and economic growth, Mimeo. Cambridge, MA: Harvard University.

Barro, R., & Lee, J, 1994, Sources of economic growth, *Carnegie-Rochester Conference Series on Public Policy* 40, 1–46.

Bartley M., Sacker A., and Clarke P., 2004, Employment status, employment conditions, and limiting illness: prospective evidence from the British household panel survey 1991-2001. *Journal of Epidemiology and Community Health* 58:501-6.

Bloom, D., & Canning, D., 2000, The health and wealth of nations, *Science* 287, 1207–1209.

Bloom, D., & Sachs, J., 1998, Geography, demography, and economic growth in Africa, *Brookings Papers on Economic Activity* 2, 207–273.

Bloom, D., Canning, D., Sevilla, J., 2004, The Effect of Health on Economic Growth: A Production Function Approach, *World Development* Vol. 32, No. 1, pp. 1–13.

Brenner, H., 1973, Mental Illness and the Economy (Cambridge: Harvard University Press.

Brenner, H., 1979, Mortality and the National Economy, *The Lancet*, 568–573.

Brenner, H., Mooney, A., 1983, Unemployment and Health in the Context of Economic Change, *Social Science Medicine* XVII, 1125–1138.

Caplin, A., and Leahy, J., 2001. Psychological Expected Utility Theory And Anticipatory Feelings, *Quarterly Journal of Economics* 166, 55–79.

Campbell, J., 1993, Intertemporal asset pricing without consumption data, *American Economic Review* 83, 487–512.

Campbell, J., 1996, Understanding risk and return, *Journal of Political Economy* 104, 298–345.

Cook, P., Zarkin, G., Crime and the Business Cycle, *Journal of Legal Studies* XIV, 115–128.

Cornell, B., What Moves Stock Prices: Another Look, *Journal of Portfolio Management* 39 (3), 32-38.

Cotti, C., Dunn, R., and Tefft, N., 2013, The Dow is Killing Me: Risky Health Behaviors and the Stock Market, *Working Paper*, University of Washington.

Cutler, David M., James M. Poterba and Lawrence Summers, 1989, What Moves Stock Prices, *Journal of Portfolio Management* 15: 4-11.

Deaton, A., 2011, The financial crisis and the well being of Americans, *The Hicks Lecture*, May 16th 2011.

Dougal, C., Engelberg, J., Garcia, D., and Parsons, C., 2012, Journalists and the stock market, *Review of Financial Studies* 25 (3):639–679.

Edmans, A., Garcia, D., and Norli, O., 2007, Sports sentiment and stock returns, *Journal of Finance* 62 (4), 1967-1998.

Epstein, L., and Zin, S., 1989, Substitution, risk aversion, and the temporal behavior of consumption and asset returns: A theoretical framework, *Econometrica* 57, 937–969.

Epstein, L., and Zin, S., 1991, Substitution, risk aversion, and the temporal behavior of consumption and asset returns: An empirical investigation, *Journal of Political Economy* 99, 263–286.

Ettner, S., 1996, New evidence on the relationship between income and health, *Journal of Health Economics*, 15(1), 67-85.

Forbes, F., McGregor, A., 1984, Unemployment and Mortality in Post-War Scotland, *Journal of Health Economics* 3, 219-257.

Grossman, M., 1972, On the Concept of Health Capital and the Demand for Health, *Journal Political Economy* 80, 223–55.

Hamermesh, D., and Soss, A., 1974, An Economic Theory of Suicide, *Journal of Political Economy* 82, 83-98.

Hamoudi, A., and Sachs, J., 1999, Economic Consequences of Health Status: A Review of the Evidence. *Working Paper No. 30. Harvard Center for International Development*, Cambridge, MA.

Hirshleifer, D., Shumway, T., 2003, Good day sunshine: stock returns and the weather, *Journal of Finance* 58, 1009-1032.

Insinga R., Ng-Mak D., and Hanson , M., 2011, Costs associated with outpatient, emergency room and inpatient care for migraine in the USA, *Cephalalgia* 31(15):1570-1575.

Juster, T., Stafford, F., 1985, Time, Goods, and Well-Being, Institute for Social Research, *University of Michigan*.

Kamstra, M., Kramer, L., Levi, D., 2000, Losing sleep at the market: the daylight savings anomaly, *American Economic Review* 12, 1000-1005.

Kamstra, M., Kramer, L., Levi, D., 2003, Winter Blues, a SAD stock market cycle, *American Economic Review* 93, 324-343.

Kahneman, D., Knetsch, J. L., and Thaler, R. H., 1990, Experimental Tests of the Endowment Effect and the Coase Theorem, *Journal of Political Economy* 98 (6), 1325-1348.

Kreps, D., and Porteus, E., 1978, Temporal resolution of uncertainty and dynamic choice theory, *Econometrica* 46, 185–200.

Krueger, A., Kahneman, D., Fischler, C., Schkade, D., Schwarz, N. and Stone, A., 2009, Time use and subjective well-being in France and the U.S., *Social Indicators Research* 93, 7-18.

Mathers C., Schofield D, 1998, The health consequences of unemployment: the evidence. *Medical Journal of Australia* 168, 178-83.

McInerney, M., Mellor, J., Nicholas, L., Recession Depression: Physical and Mental Health Effects of the Stock Market Crash, working paper, 2011.

Mehra, R., and Prescott, E., 1985, The equity premium: A puzzle, *Journal of Monetary Economics* 15, 145–161.

Morris, J., Cook D., and Shaper A.. 1994, Loss of employment and mortality, *British Medical Journal* 308:1135-9.

Nandi, A., Prescott, M., Cerda, M., Vlahov, D., Tardiff, K., and Galea, S., Economic Conditions and Suicide Rates in New York City, *American Journal of Epidemiology*, 175 (6), 527-535.

Priebe, S., Badesconyi, A., Fioritti, A., Hansson, L., Kilian, R., Torres-Gonzales, F., Turner, T., Wiersma, D, 2005, Reinstitutionalisation in mental health care: comparison of data on service provision from six European countries. *British Medical Journal* 330: 123-6.

Pritchett, L., Summers, L., 1996, Wealthier is healthier, *Journal of Human Resources* 31, 844–868.

Ruhm, C., 2000, Are Recessions Good for Your Health?, *Quarterly Journal Economics* 115, 617–50.

Seasholes, M., and Zhu, N., 2010, Individual investors and local bias, *Journal of Finance* 65, 1987–2011.

Shiller, R., 2002, Bubbles, Human Judgment and Expert Opinion, *Financial Analysts Journal* 58(3), 18–26

Strauss, J., Thomas, D., 1998, Health, nutrition, and economic development. *Journal of Economic Literature* 36, 766–817.

Schwandt, H., Wealth Shocks and Health Outcomes: Evidence from Stock Market Fluctuations, working paper, 2011.

Tolin, D., Foa, E., 2006, Sex Differences in Trauma and Posttraumatic Stress Disorder: A Quantitative Review of 25 Years of Research, *Psychological Bulletin* 132(6), 959-992.

Weil, P., 1989, The equity premium puzzle and the risk-free rate puzzle, *Journal of Monetary Economics* 24, 401–421.

Figure 1: Abnormal Hospital Admissions and the 1987 October Crash

The figure plots the abnormal hospital admissions from a regression of daily hospital admits on day of the week, year, month and holiday fixed effects (Table 2, Panel A, column 5). Abnormal admits are calculated as the % difference between the actual admissions and the admissions predicted by the regression model. Abnormal admits are plotted for the week surrounding the crash of October 1987.

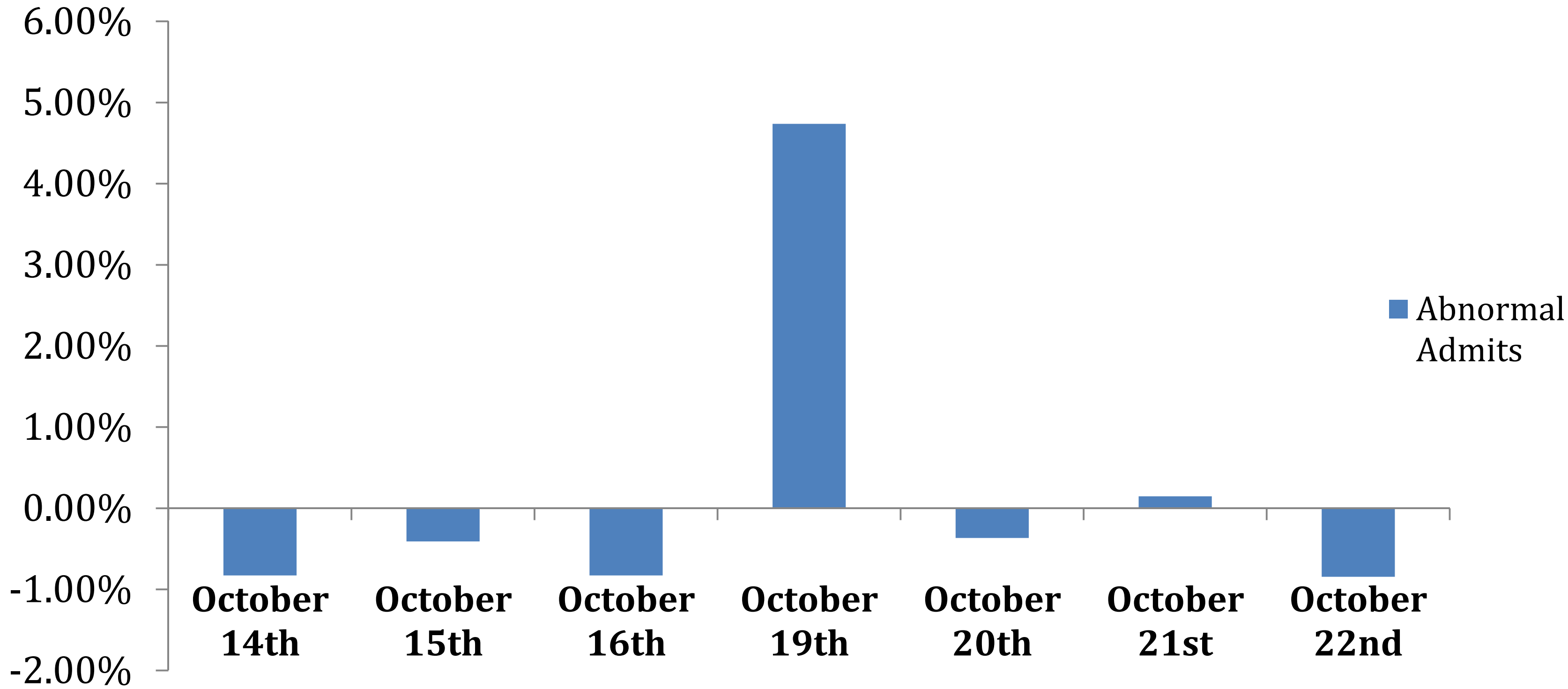

Table 1: Summary Statistics

Daily California Hospital Admits is the number of new, daily patients admitted to California hospitals. Daily California Hospital Admits by Californians is the number of new patients with a California zipcode. Daily California Hospital Charges is the sum of daily hospital charges in 2011 dollars. Daily California Hospital Admits for Mental Diseases is the number of new, daily patients admitted to California hospitals which are assigned an ICD-9 code between 290 and 319 as their primary diagnosis. Length of Stay is the number of stays a new patient stays. Daily California (Non-California) Return is the daily, value-weighted daily return of U.S. stocks with firm headquarters inside (outside) California. California Residual Return is the daily residual extracted from a regression of California Return on Non-California Return. 1-Year Volatility is the standard deviation of daily returns over the past 252 trading days.

	Mean	Standard Deviation	5th Percentile	20th Percentile	Median	80th Percentile	95th Percentile
Daily California Hospital Admits	11666	870	10276	10985	11739	12402	12925
Daily California Hospital Admits by Californians	11458	853	10085	10795	11530	12180	12691
Daily California Hospital Admits for Mental Diseases	686	78	548	621	696	752	797
Daily California Hospital Charges ($ Millions)	305	168	104	149	237	494	603
Length of Stay	5.68	47.97	1	1	3	6	16
Daily California Return	0.0011	0.0147	-0.0219	-0.0074	0.0014	0.0097	0.0223
Daily U.S. Return	0.0009	0.0110	-0.0155	-0.0053	0.0011	0.0072	0.0163
California Return - U.S. Return	0.0000	0.0054	-0.0078	-0.0030	0.0001	0.0030	0.0076
1-Year Volatility	0.0130	0.0067	0.0068	0.0080	0.0103	0.0181	0.0289

Table 2: Market Returns and New Patient Admissions in California Hospitals

The dependent variables is the natural logarithm of new, daily patients admitted to California hospitals between 1983 and 2011. The main independent variable is the daily market return to California firms. The market return is scaled by the sample standard deviation. In Panel A, day of the week, month and year fixed effects are added to columns 2, 3 and 4 respectively. Dummy variables for the week surrounding Labor Day, Independence Day, Christmas, Thanksgiving and New Years' Day (Holiday fixed effects) are included in the fifth column of Panel A. Panel B considers the predictability of the market return on day t for hospital admissions on days t-3 through t+3 (columns 1 through 7). Robust (White) standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

PANEL A

	Dependent Variable: Log(Hospital Admits)				
Market Return	-22.02***	-16.51***	-16.58***	-12.74***	-9.68***
	(7.95)	(6.51)	(6.21)	(4.23)	(3.59)
Day of the Week Fixed Effects	NO	YES	YES	YES	YES
Month Fixed Effects	NO	NO	YES	YES	YES
Year Fixed Effects	NO	NO	NO	YES	YES
Holiday Fixed Effects	NO	NO	NO	NO	YES
Observations	7,315	7,315	7,315	7,315	7,315
Adjusted R^2	0.0007	0.3105	0.3475	0.6750	0.8047

PANEL B

	Dependent Variable: Log(Hospital Admits)						
	Day t-3	Day t-2	Day t-1	Day t	Day t+1	Day t+2	Day t+3
Market Return	-4.83	-2.17	-7.39	-9.68***	-8.66**	-7.04	5.99
	(7.61)	(7.00)	(7.14)	(3.59)	(3.91)	(5.81)	(7.32)
Day of the Week Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Holiday Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Observations	7,315	7,315	7,315	7,315	7,315	7,315	7,314
Adjusted R^2	0.9352	0.9468	0.9444	0.8047	0.9578	0.9269	0.9051

Table 3: Alternate Specifications

The dependent variable in column 1 is the natural logarithm of two-day hospital admissions (Day t and Day t+1) in the state of California. Column 2 is identical to column 1 except the market return for California firms is scaled by a rolling one-year standard deviation. Column 3 is identical to column 2 except the dependent variable subtracts off the natural logarithm of the prior two-day admission (Days t-1 and t-2). The dependent variable in column 4 (5, 6) subtracts off a rolling 1-month (6-month, 12-month) average of the dependent variable. All independent variables are the same as in Table 2. Newey-West standard errors with one lag are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable: Log(Hospital Admits on Day t, t+1)					
		Rolling Standard Deviation	Minus Day t-1, t-2 admits	Minus 1-month rolling average	Minus 6-month rolling average	Minus 12-month rolling average
Market Return	-9.12***	-13.53***	-11.49**	-13.27***	-14.04***	-13.95***
	(3.21)	(3.59)	(5.69)	(3.71)	(3.66)	(3.66)
Day of the Week Fixed Effects	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Holiday Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	7,315	7,315	7,315	7,315	7,315	7,315
Adjusted R^2	0.9281	0.9282	0.9723	0.9151	0.9144	0.9152

Table 4: Extreme Returns

The first two columns reproduce Table 3, Column 2 but break the main independent variable (Market Return) into quintiles. Column 1 has only the bottom quintile. Column 2 has each quintile (the omitted quintile is the middle one). The last two columns are identical to the first two except the dependent variable is hospital charges (rather than hospital admits). Newey-West standard errors with one lag are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable:			
	Log(Hospital Admits on Day t, t+1)		Log(Hospital Charges on Day t, t+1)	
Market Return: Bottom Quintile	31.33***	31.41***	37.00**	45.21**
	(9.15)	(11.89)	(14.61)	(19.16)
Market Return: Quintile 2		4.81		-4.7
		(11.69)		(18.21)
Market Return: Quintile 4		-0.456		19.28
		(14.1)		(23.65)
Market Return: Top Quintile		-3.93		18.02
		(11.62)		(17.86)
Day of the Week Fixed Effects	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Holiday Fixed Effects	YES	YES	YES	YES
Observations	7,315	7,315	7,315	7,315
Adjusted R^2	0.9281	0.9281	0.9956	0.9956

Table 5: Hospital Admissions for Psychological Conditions

The dependent variables is the natural logarithm of new, daily patients admitted to California hospitals between 1983 and 2011 on Day t (columns 1-4) and Day t+1 (columns 5 – 8). In columns 1, 2, 5 and 6 we exclude all patients admitted where the primary diagnosis related to mental health, i.e. those with ICD-9 codes between 290 and 319. In columns 3, 4, 7 and 8 we only consider patients admitted where the primary diagnosis is related to mental health. Market Return and the market returns quintiles are the same as in Table 4. Robust (White) standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable: Log(Hospital Admits Day t)				Dependent Variable: Log(Hospital Admits Day t+1)			
	Non-Mental Disorders		Mental Disorders		Non-Mental Disorders		Mental Disorders	
Market Return	-13.45***		-21.37***		-13.92***		-3.17	
	(4.04)		(7.05)		(4.11)		(0.41)	
Market Return: Bottom Quintile		24.57*		57.86**		25.84**		26.12
		(13.26)		(22.64)		(12.71)		(27.33)
Market Return: Quintile 2		-11.37		26.47		8.51		9.55
		(13.00)		(21.69)		(12.80)		(25.44)
Market Return: Quintile 4		-8.35		2.17		-0.07		8.34
		(13.51)		(24.54)		(14.19)		(31.25)
Market Return: Top Quintile		-11.25		1.93		-1.07		17.57
		(13.21)		(21.66)		(12.00)		(25.18)
Day of the Week Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Holiday Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,315	7,315	7,315	7,315	7,315	7,315	7,315	7,315
Adjusted R^2	0.7981	0.8141	0.7442	0.7441	0.9568	0.9616	0.9090	0.9090

Table 6: Hospital Admits and News

The dependent variable in column 1 is the natural logarithm of two-day hospital admissions (Day t and Day t+1) in the state of California. The first column reproduces column 1 of Table 4 where the main independent variable is a binary variable that takes the value 1 if returns are in the bottom quintile. Column 2 is identical to column 1 except the bottom quintile dummy turns on if returns are in the bottom quintile and there is no news of a war or terrorist attack. Column 3 is identical to column 1 except the bottom quintile dummy turns on if returns are in the bottom quintile and there is no news event. See section IV.b for a discussion of the news classifications. Newey-West standard errors with one lag are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable: Log(Hospital Admits on Day t, t+1)		
Bottom Quintile: All	31.33*** (9.15)		
Bottom Quintile: No Wars/Terrorist Attacks		31.65*** (9.29)	
Bottom Quintile: No News Event			31.71*** (12.05)
Day of the Week Fixed Effects	YES	YES	YES
Month Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Holiday Fixed Effects	YES	YES	YES
Observations	7,315	7,315	7,315
Adjusted R^2	0.9281	0.9281	0.9281

Table 7: Hospital Admits and Location

The dependent variables is the natural logarithm of new, daily patients admitted to California hospitals between 1983 and 2011 on Day t and Day t+1. Non-California Return is the daily, value-weighted daily return of U.S. stocks with firm headquarters outside California normalized by a rolling (1-year) standard deviation. Non-California Return: Bottom Quintile is a dummy variable which takes the value of 1 when Non-California Return is in the bottom quintile. Newey-West standard errors with one lag are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable: Log(Hospital Admits on Day t, t+1)	
Non-California Return	9.29*** (3.59)	
Non-California Return: Bottom Quintile		35.91*** (9.38)
Day of the Week Fixed Effects	YES	YES
Month Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Holiday Fixed Effects	YES	YES
Observations	7,315	7,315
Adjusted R^2	0.9281	0.9282