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 (within the same day), suggesting that *anticipation* over future consumption directly influences instantaneous utility, e.g., Caplin and Leahy (2001). Moreover, the effect of such anticipation is path dependent, being strongest during low volatility regimes, and immediately following low returns.

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 and end unto itself," psychological distress among investors is especially relevant for financial economists, for whom the process of price formation is of central importance.

However, 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 has on the first part of the feedback loop. We aim to fill this gap, and accordingly, look for a causal relationship between stock price fluctuations and investor psychology.

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[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). See Baker and Wurgler (2007) for a comprehensive review on investor sentiment and the stock market.

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 gyrations in stock prices impact an investor's instantaneous utility, the more likely the effect is coming through <u>expectations</u> over future consumption, rather than via <u>current</u> consumption, i.e., through the budget constraint. The distinction plays a central role in modern asset pricing theory, indeed being the defining feature of "recursive" preference, but identifying the utility impact of expectations 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] This measure has the benefit not only of being revealed versus self-reported, but also because it is constructed at daily intervals, facilitates causal inferences. We then form portfolios of stock returns that we think are relevant for California-based investors: 1) a broad-based market index, and 2) an index consisting only of local companies. Time series regressions tell us whether, and how quickly, the stock market impacts investor psychology.

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

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

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 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 U.S. stock prices (roughly -1.5%) increases admissions to California hospitals by about 0.26% over the next two days.[3] When we restrict our sample to health conditions that are primarily psychological in origin such as anxiety or panic attacks, we find an even quicker and more dramatic 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.

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-related conditions do not result in hospitalization; however, the following back-of-the-envelope calculation provides at least some context for judging the size of the effect. A daily return in the bottom quintile increases hospital admissions by 0.63% over the next two days. In California, 11,665 people are hospitalized each day implying approximately (20%)(.0063)(11,665)(252 trading days) ≈ 3,700 market-induced hospitalizations a year. Combining this with estimates from 2009 U.S. Census Bureau estimates indicating that single,

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[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 low stock returns but high rates of illness.

average hospitalization event costs roughly $21,000, stock market declines increase health care costs by at least $77 million in California, which extrapolates to approximately $650 million annually in the U.S.[4]

Both in terms of novelty and economic substance, the immediacy of the result – stock market declines *today* result in psychological distress *today* – is the most significant aspect of our analysis. Indeed, the relation between economic growth and health (both somatic and mental) has been studied for at least four decades,[5] 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.[6] In most cases, improving economic conditions are associated with better health, although see Ruhm (2000) for evidence that increases in income can lead to less healthy behaviors like smoking and drinking.

Left unresolved is whether any causal effects manifest through changes in the agent's budget constraint, and therefore impact instantaneous utility by altering current consumption, or whether expectations of future consumption directly impact her current well-being, independent of current consumption.

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[4] Total health care expenditures totaled over $2.4 trillion in 2009, with hospital care comprising 31% ($759 billion) of this sum. Roughly 36 million people were hospitalized in 2009, with an average stay of 4.9 days. Source: U.S. Census Bureau, Statistical Abstract of the United States (2012): http://www.census.gov/compendia/statab/2012/tables/12s0134.pdf

[5] 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.

[6] 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.

More specifically, one can imagine a number of reasons why becoming poorer might adversely influence health (or utility generally), such as diet, physical activity, health insurance status, ability to pay for medications, and so on. All of these, however, reflect changes in expenditures, and therefore, take at least some time – presumably more than a few hours – to manifest, especially to a degree sufficient to justify hospital admission.

Accordingly, our results point to a second, distinct way that wealth fluctuations impact instantaneous utility: through expectations of future consumption. 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,[7] where instantaneous utility depends, in part, on the agent's expectation of future consumption.

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 enter into the utility function, our results suggest that incorporating the

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[7] 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).

impact of anxiety or other anticipatory emotions into asset pricing models may be realistic.

In the remainder of the paper, we take as given that investors worry about the stock market, and ask *when* and *why*. Regarding the first question, we test whether market conditions have either an attenuating or amplifying effect on investors' collective psychological reactions to stock price movement. Over short horizons, we find that consecutive sequences of market declines are particularly painful for investors: the effect of a stock market decline today is twice as strong when yesterday's market was also down. Over longer horizons, the effect of a large market decline today is twice as strong in low-volatility regimes, when extreme returns are more surprising to investors. To the extent that our benchmark results provide evidence that investor expectations influence instantaneous utility, these extensions suggest a path dependence in this relation.

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 comparing the health sensitivities to California-based and non-California based firms. Here, we find that investors seem to care about <u>both</u> the prospects of local companies – for whom job or income growth is likely the dominant consideration – as well as those headquartered far away (particularly large firms), where the portfolio effect is most likely strongest.

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?"[8] 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

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

self-reported, and is thus not subject to the usual problems of survey data.[9]

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 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 far underestimate any actual 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.

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[9] 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).

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 together 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 contained in its ranks. Volatility also varies over time, which will be important in some of our tests. 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* is some measure of 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, standardized by the trailing one-year standard deviation of this series. However, in extensions, we explain *admissions*

as a function of alternative return series which include returns outside of California.

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 in certain geographical areas, or 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.[10]

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[10] 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.

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 ultimately allow us to make this distinction.

Finally, the vector of *controls* in equation (1) accounts for the fact that hospital admissions 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 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.

b. Results

In Panel A of Table 2, we show our main result, progressively adding in *control* variables across columns. For now, 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 -30 basis points, with a *t*-statistic of -3.4. Moving to the right, addition of either *day of the week fixed effects* (column 2) or *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 a little more than -16 basis points, which settles to -13 basis points (*t*=-3.4) 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 the columns, the data clearly reject all cases in which health outcomes lead the stock market. For all cases in which $\tau < 0$, our estimates for α are both small in absolute value, and statistically insignificant. However, this changes abruptly in the fourth and fifth columns, the former of which we have already seen in Panel A, and the latter of which is new. 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 ($\approx$-1.4%) in the stock returns of California-based companies increases daily hospital admissions by about .26%.

One question that arises immediately from the results in Table 2 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 Table 3 we allow for *return* to enter through a series of dummy variables, one for each quintile in the empirical distribution. In both columns 1 (no time *controls*) and 2 (with time *controls*), we see that only returns in the bottom quintile impact hospital admissions. Taking the model with time *controls* as the most indicative of the underlying behavior, once a week on average, the market drops by enough to put an additional .27% (.36%) patients in the hospital on day 0 (day 1), for a combined effect of .63%.

Given that between 11,000 and 12,000 people are hospitalized in California daily, the annualized impact of a "bottom quintile" return (i.e., that occurring 20% of the time) is somewhere between 3,500 to 4,000 additional hospitalizations. Given that the typical hospital visit costs over $20,000 on average (per the 2009 U.S. Census Bureau), this implies an additional health care burden in the neighborhood of $70-$80 million in California, or about ten times that amount extrapolating to the entire U.S.

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. allowing us to triple these estimates to arrive at about $2 billion. [11] However, even this is likely a very conservative estimate of the psychological burden, given that the percentage of

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[11] 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

these costs seen in hospital settings must be substantially lower. As a specific example, 36 million Americans suffer from migraine headaches.   In 2010, the cost of inpatient hospitalizations for migraines was a paltry $375 million compared to the cost of outpatient visits which totaled $3.2 billion (Insinga, Ng-Mak, and Hanson, 2011).

c. 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).[12] 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.

Table 4 reports the results and indicates that the stock-market/health relation is approximately twice as large for these disorders.   Columns 1 and 3 indicate that in the simplest linear specification a one standard deviation drop in the stock market corresponds to a 12.1 bps increase in hospitalizations for non-mental health codes but a 21.4 bps increase in hospitalizations related to mental health. The results are more pronounced when we examine extreme returns (columns 2 and 4).   In fact, we find no statistically detectable relationship between non-mental conditions and bottom-quintile returns; however a bottom-quintile return immediately corresponds to a 57 bps spike in hospitalizations for mental conditions (p-value < .05).

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

d. Path Dependence

One question that naturally arises is whether investors are more or less troubled by market declines during certain times. For example, declines in one's portfolio might be especially painful if directly preceded by poor performance. In this section, we explore such path dependence of investor's health responses, both over long and short horizons.

Our first test explores path dependence over relatively long time periods, asking whether a given percentage drop in an investor's portfolio is influenced by the volatility of stock prices over the previous year. Recall that our benchmark specification already standardizes by the one-year trailing volatility, which we reproduce for comparison in column 1 of Table 5. By contrast, in column 2, we use the entire 28-year sample to calculate the standard deviation, and thus ignore any asymmetric effects between high and low volatility regimes. As seen, the coefficient drops in both economic and statistical significance when we ignore time-varying volatility effects, suggesting that investors evaluate declines in their portfolio in a relative, rather than absolute, sense.

The comparisons in the next two columns make this even clearer, where we split the sample based on whether the trailing one-year volatility is above or below the median (1.03%), but calculate quintile cutoffs based on the entire 28-year sample. When volatility is relatively high (column 3), our estimates suggest that a market return in the bottom quintile increases day t hospitalizations by roughly 22 basis points, which is statistically insignificant. By contrast, column 4 indicates that during low volatility regimes, a return in the bottom quintile increases hospital admissions by over 50 basis points ($p<.05$).

One plausible explanation for this finding is that investors use recent market performance to form estimates of future volatility. Given that volatility is persistent, experiencing high and low "regimes" (Hamilton and Susmel (1994)) an extremely low return – say negative three percent in a day – during a relatively non-volatile period likely signals a regime shift to a period of higher volatility. If investors care about the volatility of their future consumption in addition to its level (more discussion about what we can infer from investor preferences in Section IV.), they may become distressed.

A second kind of path dependence operates over shorter horizons. In columns 5 and 6 of Table 5 we divide the sample of trading days into two groups: those when the market was up on day *t-1* (column 5) and those when the market was down on day *t-1* (column 6). A bottom quintile return on day 0 following a down market on day *t-1* is nearly twice painful (45.93 bps) for investors than a bottom quintile return on day 0 which followed an up market on day *t-1* (28.13 bps). This is more evidence that investors judge today's decline relative to recent market behavior rather than its absolute effect on future consumption.

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 utility – 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 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 happiness 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 for them. 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 consumption is not observable, making it difficult to rule out the contemporaneous consumption channel, or 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 utility. 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, strongly suggest 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).

3. Finally, capturing the full impact of expectations on investors' current utility requires accounting for *histories*, both over short and long horizons. Returning to Equation (3), this suggests that a full

characterization of investor preferences prescribes that $f()$ take into account prior information ($<t$), such as recent price histories or volatility.

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.[13] 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 (e.g., Caplin and Leahy (2001)).

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 utility 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 income or job growth.

Is this distinction important? Perhaps not, given that the implications for health are identical, and that this issue is ultimately about little more than capitalization – i.e., whether investors care more about losing a dollar *already*

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[13] 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.

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 closing the price-sentiment feedback loop alluded

to in the introduction, prices *per se* as a source of investor sentiment is

important. Because we view these as interesting implications, we attempt to be

more precise about the specific source of investor distress when stock prices

decline.

    The ideal experiment would be to isolate variation in stock prices that is

completely decoupled from the arrival of economic news. Although isolated cases

probably exist – e.g., the October Crash of 1987 is widely attributed to correlated

trading algorithms across institutional investors rather than the arrival of news –

this is clearly not the norm. However, there are two sources of variation that

allow us to make some headway distinguishing between what we will call

"portfolio" and "non-portfolio" wealth shocks. Our first test holds constant the

return series and varies the patient population, while the second fixes the

population but varies the return series.

    Specifically, the first two columns of Table 6 compare the effect of

California returns on patients in California hospitals which provide a California

zip code as their living address to those who do not. The result is immediate:

California returns only seem relevant for native Californians. A one-standard

deviation decrease in California returns increases hospital admissions for

Californians by 13.71 bps (p-value < .01) but has a negligible effect with the

opposite sign (2.33 bps) for non-Californians. While it is remarkable that we find

no effect of California returns on non-Californians, it's worth noting that non-Californians which arrive at California hospitals are a very small group. According to Table 1 they constitute less than 2% of hospital admissions.

For our second test, we consider the entire sample but compute the daily return to all companies not located in California (called *Non-California Return* in Table 6, column 3). The reason we consider non-local company returns is that although investors are known to disproportionately own local stocks, the majority of portfolio wealth is held outside of local companies.[14] For example, Seasholes and Zhu (2010) examine individual investor portfolios and find, on average, investors hold about 30% of their portfolio locally (within a 250-mile radius) and 70% remotely (outside the 250 mile radius). Thus, while California returns should be informative about California jobs, real estate prices, and other sources of wealth for Californians, the effect of non-California returns on Californians should primarily be through their portfolios. This will allow us to say something meaningful about portfolio vs. non-portfolio effects on health outcomes.

When we consider the effect of non-California returns on California hospital admissions we find a positive and significant coefficient of -9.05 bps (p-value < .05). While this is certainly smaller than the effect we find in the main specification which relates California returns to admissions (-13.44) it suggests non-local portfolio effects are at least part of the wealth-health relation.

Of course, they are not the only part. For our final specification, we first regress non-California returns on California returns and extract a residual. This

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[14] Over our sample period, California-based companies represented about 14% (peaking at 15% in 2001) of all public firms listed on CRSP by number, and about 12% by market capitalization (peaking in at 20% in 2000).

residual represents the component of market returns that are uniquely Californian, i.e. with the common component removed. When we place non-California returns and the California residual in the same specification (column 4) both are economically and statistically significant. The coefficient on non-California returns is -9.96 (p-value < .05) and the coefficient on the California residual is -11.20 (p-value < .01). Taken together the results suggest both portfolio and non-portfolio effects are responsible for the wealth-health relation we document.

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. Stock performance of locally headquartered companies is a particularly important determinant of physical health, suggesting that concern related to human capital (e.g., employment, wages) is of special concern.

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.

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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.
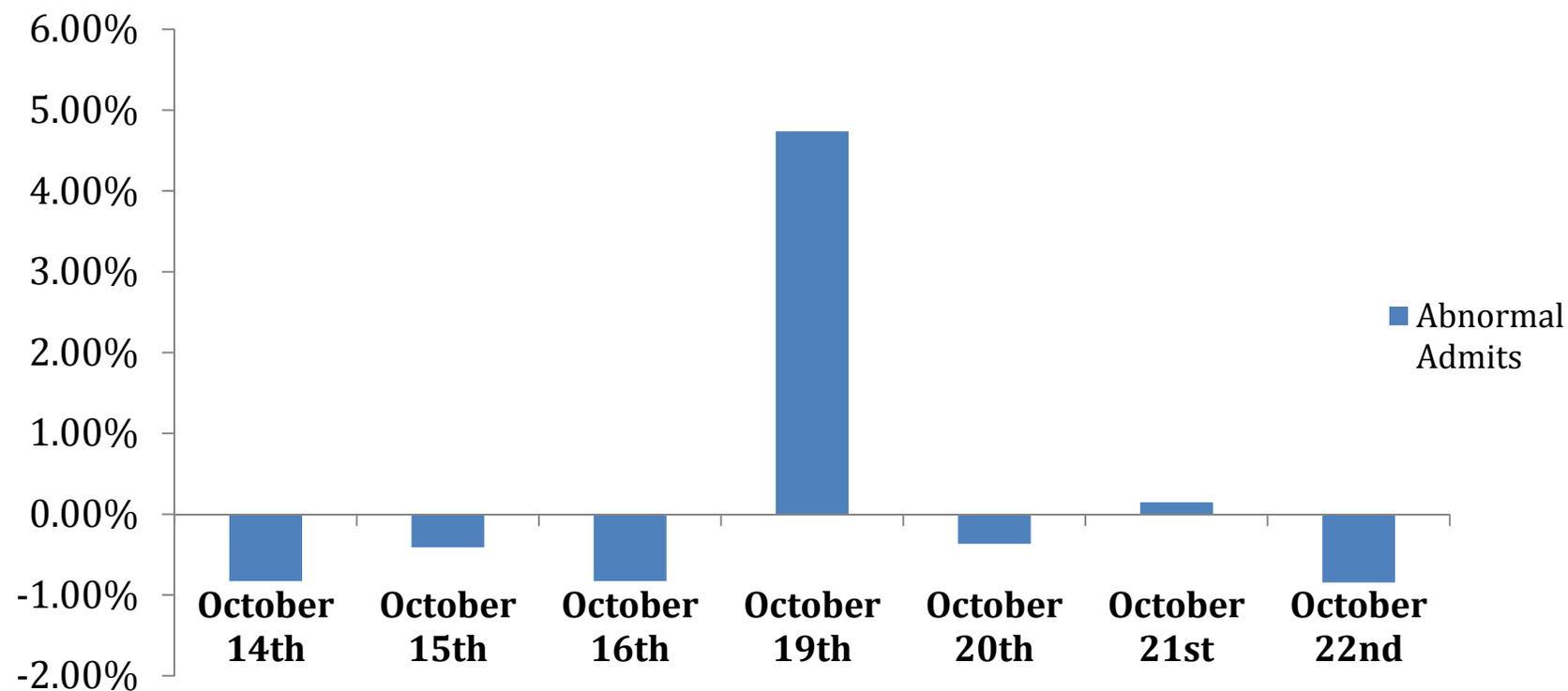
Table 1: Summary Statistics

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 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	11665	877	10275	10985	11739	12402	12925
Daily California Hospital Admits by Californians	11457	860	10085	10795	11530	12180	12691
Daily California Hospital Admits for Mental Diseases	686	78	548	621	696	752	797
Length of Stay	5.68	47.97	1.00	1.00	3.00	6.00	16.00
Daily California Return	0.0011	0.0147	-0.0218	-0.0074	0.0014	0.0097	0.0223
Daily Non-California Return	0.0009	0.0110	-0.0155	-0.0053	0.0011	0.0072	0.0163
California Residual Return	0.0000	0.0072	-0.0096	-0.0035	0.0000	0.0035	0.0093
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 a rolling 1-year 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	-29.89***	-26.55***	-27.87***	-16.51***	-13.44***
	(8.76)	(7.12)	(6.89)	(4.66)	(4.00)
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	7,319	7,319	7,319	7,319	7,319
Adjusted R²	0.0014	0.3114	0.3483	0.6747	0.8033

PANEL B

	Day t-3	Day t-2	Day t-1	Day t	Day t+1	Day t+2	Day t+3
	Dependent Variable: Log(Hospital Admits)						
Market Return	-5.44	2.27	-6.56	-13.44***	-12.78***	-8.94	6.96
	(7.75)	(7.23)	(7.44)	(4.00)	(4.08)	(5.75)	(7.46)
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	7,319	7,319	7,319	7,319	7,319	7,319	7,319
Adjusted R²	0.9351	0.9466	0.9442	0.8033	0.9577	0.9269	0.9051

Table 3: Extreme Returns

The dependent variables is the natural logarithm of new, daily patients admitted to California hospitals between 1983 and 2011. This table reproduces Table 2 but breaks the main independent variable (Market Return) into quintiles. The omitted quintile is the middle one. In the first column, no fixed effects are added. In the second column day of the week, month, year and holiday fixed effects are added. Robust (White) standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable: Log(Hospital Admits)	
Market Return: Bottom Quintile	143.83***	27.23**
	(28.61)	(13.04)
Market Return: Quintile 2	32.908	-6.9477
	(29.86)	(12.77)
Market Return: Quintile 4	4.298	-6.1245
	(30.04)	(13.68)
Market Return: Top Quintile	48.28	-7.7255
	(29.83)	(12.98)
Day of the Week Fixed Effects	NO	YES
Month Fixed Effects	NO	YES
Year Fixed Effects	NO	YES
Holiday Fixed Effects	NO	YES
Observations	7,319	7,319
Adjusted R²	0.0038	0.8032

Table 4: Hospital Admissions for Psychological Conditions

The dependent variables is the natural logarithm of new, daily patients admitted to California hospitals between 1983 and 2011. In columns 1 and 2 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 and 4 we only consider patients admitted where the primary diagnosis related to mental health. Market Return is the daily market return to California firms. Columns 2 and 4 break Market Return into quintiles. The omitted quintile is the middle one. Robust (White) standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

| | Dependent Variable: Log(Hospital Admits) | | | |
	Diseases Excluding Mental Disorders		Mental Disorders	
Market Return	-12.12***		-21.38***	
	(4.12)		(7.05)	
Market Return: Bottom Quintile		21.92		57.01**
		(13.77)		(22.70)
Market Return: Quintile 2		-13.58		24.81
		(13.53)		(21.79)
Market Return: Quintile 4		-10.74		0.87
		(14.32)		(24.64)
Market Return: Top Quintile		-8.45		-0.7090
		(13.98)		(21.76)
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	7,319	7,319	7,319	7,319
Adjusted R²	0.7938	0.7938	0.7441	0.7441

Table 5: Path Dependence and the Stock Market-Health Relation

The dependent variable 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. In the first column, the market return is scaled by a rolling 1-year standard deviation (Dynamic Std). In the second column it is scaled by the standard deviation over the entire sample (Static Std). Market Return: Bottom Quintile is a dummy variable which takes the value of one if the Market Return was in the bottom quintile of all returns in the sample. Column 3 (4) considers the subset of observations where the daily standard deviation over the past year was above (below) the median. Column 5 (6) considers the subset of observations where the t-1 market return was above (below) zero. Robust (White) standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

			Dependent Variable: Log(Hospital Admits)			
			High Volatility	Low Volatility	Market Up Yesterday	Market Down Yesterday
Market Return	-13.44***					
	(4.00)					
Market Return: Static Std		-9.26**				
		(3.61)				
Market Return: Bottom Quintile			22.36	52.11**	28.13	45.93***
			(14.60)	(24.01)	(17.32)	(17.77)
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	7,319	7,319	3,660	3,659	3,172	4,147
Adjusted R²	0.8033	0.8033	0.7813	0.8204	0.8027	0.8056

Table 6: Hospital Admits and Location

The dependent variables is the natural logarithm of new, daily patients admitted to California hospitals between 1983 and 2011. The first (second) column considers only patients with zipcodes outside (inside) the state of California. 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. All three return variables are normalized by a rolling (1-year) standard deviation. Robust (White) standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Dependent Variable: Log(Hospital Admits)			
	Non-Californians	Only Californians	All	All
California Return	2.33	-13.71***		
	(10.23)	(4.01)		
Non-California Return			-9.05**	-9.96**
			(3.96)	(4.01)
California Residual Return				-11.20***
				(3.94)
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	7,319	7,319	7,319	7,319
Adjusted R²	0.5906	0.8027	0.8026	0.8028