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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 to 2011, we find a strong inverse link between daily stock returns and hospital admissions, particularly for psychological conditions such as anxiety, panic disorder, and major depression. The effect is nearly instantaneous (within the same day) for psychological conditions, suggesting that *anticipation* over future consumption directly influences instantaneous utility.

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 to these questions. First, to the extent 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] Put differently, even taking as given Hamoudi and Sachs's (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.

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[1] Abundant evidence shows 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 (Hirshleifer and Shumway (2003)), hours of daylight (Kamstra, Kramer, and Levi (2003)), and disruptions in sleep patterns (Kamstra, Kramer, and Levi (2000, 2002)). See Baker and Wurgler (2007) for a comprehensive review of investor sentiment and the stock market.

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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 this feedback loop. In this paper we seek a relationship between stock price fluctuations and investor psychology.

Third, the speed with which psychology affects prices can be informative about aspects of investor preferences that are difficult to infer outside the laboratory. Specifically, the more quickly that changes in stock prices impact an investor's instantaneous well-being, the more likely the effect is coming through *expectations* over future consumption, rather than through *current* consumption, that is, the budget constraint. This distinction plays a central role in modern asset pricing theory—indeed, it is the defining feature of recursive preferences—but identifying the effect of expected consumption is challenging outside the laboratory.

To address the above questions, we first obtain admission records for every California hospital each day from 1983 until 2011. Our proxy for the real-time psychological well-being of 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, and major depression.[2] We next form portfolios of stock returns that are likely relevant for California-based investors: an index consisting of local companies. Time-series regression analysis then indicates whether, and how quickly, the stock market impacts the psychological well-being of investors.

Figure 1 provides an illustration. In particular, the figure 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% on Black Monday. Further, there is neither a delayed effect nor a reversal, despite the fact that, on October 20, about half of the previous day's losses were erased. The first result indicates an immediate impact of market fluctuations on the psychological states of investors; the second suggests an asymmetric impact, whereby the decrease in utility following market declines outweighs any increase in utility after price run-ups.

Both of these findings generalize over our three-decade sample. In time-series regressions we find that, on average, a one *SD* decrease in California stock prices (roughly –1.5%) increases admissions to California hospitals by 0.18% to 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

[2] Because psychological stress can manifest in 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.

[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, for example, January being simultaneously associated with high stock returns but low rates of illness.

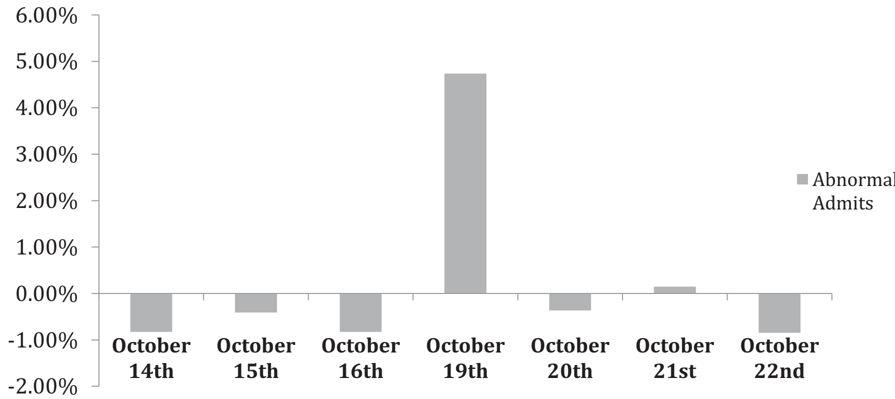

Figure 1. Abnormal hospital admissions and the October 1987 crash. The figure plots abnormal hospital admissions from a regression of daily hospital admits on day of the week, year, month, and holiday fixed effects (Table II, Panel A, column (5)). Abnormal admits are calculated as the percent difference between actual admissions and the admissions predicted by the regression model. Abnormal admits are plotted for the week surrounding the crash of October 1987.

as anxiety or panic attacks, we find that the response is both quicker and stronger—virtually the entire effect shows up the first day (as with the October 1987 crash), with a magnitude roughly twice that observed for nonpsychological disorders. Moreover, when we separate the market return into quintiles, we find that investors only respond to return shocks in the lowest quintile. There is no corresponding decrease in hospitalizations following extreme market increases.

How great is the additional healthcare burden caused by stock market fluctuations? This question 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 that market declines are associated with at least $100 million in additional annual hospital-related expenses for Californians, though again, the true effect is undoubtedly larger.

The relation between economic growth and health has been studied for at least four decades,[4] including recent work by Schwandt (2014), McInerney, Mellor, and Nicholas (2013), Nandi et al. (2013), Deaton (2012), and Cotti, Dunn, and Tefft (2015), with causation often going in both directions.[5] Most studies

[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 (1985), 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), and 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., Morris, Cook, and Shaper (1994), Mathers and Schofield (1998), Bartley, Sacker,

find a positive association between economic conditions and health, although Ruhm (2000) reports 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 losing money itself lead to a negative physiological response?

The immediacy of the effect—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 from both a trip to the dentist's office today and the thought of going to the dentist tomorrow, an investor's well-being appears to depend 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] whereby instantaneous utility depends at least in part on the agent's expectation of future consumption.

Of the studies that employ recursive utility, 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 shed light on 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 nontraded types of wealth? Although difficult to distinguish completely between such portfolio and nonportfolio considerations, we gain some insight by examining whether investor reactions to market declines concentrate on days when important economy-wide news is released.

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

The remainder of the paper is organized as follows. Section I describes the sources for our health and stock market data. In Section II, we present our main result that stock market fluctuations predict real-time changes in health, both

and Clarke (2004)). However, in many cases, it is hard to distinguish between deteriorating health as 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 (1996), Hansen and Hansen, Sargent, and Tallarini (1999), Tallarini (2000), Bansal and Yaron (2004), Hansen, Heaton, and Li (2005), Colacito and Croce (2011), and Croce (2014).

mental and otherwise, and report evidence of path dependence. In Section III, 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 decline. We conclude in Section IV.

I. Measurement and Data

A. Physical Health and Investor Distress

Our tests require an empirical proxy for the real-time utility, or general well-being, of investors at any given point in time. Economists have long wrestled with how best to measure what is inherently a subjective quality for decades. This work has generally resulted 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 to 10, how would you rate your stress level?"[7] The second is to observe or record behavior, and use these measurements to infer subjective well-being. A recent example is Krueger et al. (2009), who employ 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 has 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 further insights 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 to make somewhat general if not conservative estimates of the overall health costs implied by stock market declines.

On the other hand, our approach suffers some offsetting disadvantages. Perhaps most important among them is the fact that hospitalizations are fairly rare, occurring only in situations in which acute medical attention is warranted. Because fluctuations in a person's mental or physical well-being (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 in which people's physical or mental health experiences sufficiently deteriorate to justify hospital admission. Consequently, if a rising market *improves* collective mood, we will capture this effect only to the extent that hospitalizations decline. Thus, whatever the statistical power of this

[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 asked about whether caring for an elderly parent is enjoyable).

approach, it is clearly inferior to a measure that directly captures variation in 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" hereafter) 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 for 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. 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 take ICD-9 codes in the 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 data sets 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 California or not in California.

We merge the hospital admission data with the return data, which results in approximately 252 observations (trading days) per year. For example, for the market return on March 11, 2010, day t hospital admissions are those that occurred on March 11, 2010. Day $t + 1$ corresponds to March 12, 2010, and day $t + 2$ corresponds 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 $t + 1$ corresponds to a trading day but day $t + 2$ does not.

Table I provides summary statistics for our variables of interest. During our sample period, the average number of new admits to California hospitals was

Table I

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 zip code. *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 that 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 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*. *One-Year Volatility* is the *SD* of daily returns over the past 252 trading days.

	Mean	*SD*	5th Percentile	20th Percentile	Median	80th Percentile	95th Percentile
Daily California Hospital Admits	11,666	870	10,276	10,985	11,739	12,402	12,925
Daily California Hospital Admits by Californians	11,458	853	10,085	10,795	11,530	12,180	12,691
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 Residual Return	0.0000	0.0054	−0.0078	−0.0030	0.0001	0.0030	0.0076
One-Year Volatility	0.0130	0.0067	0.0068	0.0080	0.0103	0.0181	0.0289

11,665 per day, with a *SD* of 877. Unsurprisingly, native Californians comprise the vast majority of these admits (98%). Six percent of all hospital admissions are for reasons related to mental health, which corresponds to an average of 686 new mental health patients per day. The typical hospital patient stays for 5.68 days, with a distribution that is highly skewed: the median stay is three days but the *SD* is 48 days, due to a handful of extremely long hospital stays.

During our sample 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 (*SD* 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 *SD* of 252 trailing daily California returns was 103 basis points, but for 5% of our observations this volatility reaches as high as 289 basis points.

II. 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:

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

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 *SD* of *return*. We also present results for alternative specifications. For instance, we scale *return* and *admission* by their corresponding rolling *SD*. We also consider various patient populations. In most cases we aggregate across the entire state of California, but we also examine our results for select subsets, such as patients suffering from particular medical conditions.

The subscripts in equation (1) are worth mentioning. Recall from Section I 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 ($\tau = 0$) between *returns* and *admissions*, but matters when testing for either a leading or lagging relation.

Following the notation above, $\tau = +1$, $+2$, and $+3$ allow us to test for a leading relation between the stock market and health variables, in particular, whether returns up to three days ago influence hospital admissions today. This could occur if investors demonstrate *delayed awareness*, that is, if they do not pay close attention to day-to-day movements in stock prices but instead become aware of such changes over the course of a few days. Another possible explanation is *delayed reaction*, whereby investors are immediately aware of market conditions but the consequences for their health take time to manifest.[9]

Negative values for τ, in contrast, allow us to test for a lagging relation between health outcomes and stock market performance. Such a relation 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

[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.

that health conditions are simply a proxy for sentiment and work not through fundamentals but rather through price pressure effects, combined with limits to arbitrage. Our tests permit us to distinguish these possibilities.

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 include indicator variables for the three days surrounding each of the following holidays: New Year's 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, inclusion of these controls increases the model's overall fit and statistical precision.

B. Results

In Panel A of Table II, we present our main result and progressively add control variables across columns. We first estimate equation (1) with τ set to zero, that is, ignoring any lead or 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)) decreases the coefficient to –17, but month fixed effects (column (3)) appear to have minimal impact on the estimated coefficient, apart from increasing its precision. Including year effects (column (4)) matters more, reducing the coefficient to about –13 basis points, which settles to –10 basis points ($t = -2.7$) after we include holiday fixed effects (column (5)).

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 consistently reject the conjecture that 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 former of which we have already seen in Panel A. Comparing these estimates, it appears that about half of the effect of stock market fluctuations on health shows up the same day as the fluctuations and recurring effect showing up the next day. Together, a

[10] Although not statistically significant, we note that the magnitude of the coefficient when $\tau = -1$ is larger than when $\tau = -2$ or $\tau = -3$. Some of this may reflect the fact that returns are measured from close-to-close (i.e., 1 p.m. PST to 1 p.m. PST the next day) and hospitalizations are measured from midnight to midnight (PST). Thus, investors may be reacting to information released after markets close (1 p.m. PST) but before midnight PST, such as earnings announcements.

Table II

Market Returns and New Patient Admissions in California Hospitals

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. The market return is scaled by the sample *SD*. 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 Year's 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) to (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)

	(1)	(2)	(3)	(4)	(5)
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 $t-3$ (1)	Day $t-2$ (2)	Day $t-1$ (3)	Day t (4)	Day $t+1$ (5)	Day $t+2$ (6)	Day $t+3$ (7)
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

one *SD* decline (≈–1.4%) in the stock returns of companies headquartered in California increases daily hospital admissions by about 0.18%.

Table III 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 II, Panel B). The controls are the same as in Table II, and we calculate Newey-West standard errors with one lag because the overlapping (two-day) dependent variable creates autocorrelation in the residuals. Thus, column (1) of Table III is simply an aggregation of columns (4) and (5) (days t and $t+1$) in Table II, Panel B and hence it is no surprise that the coefficient on *return* in column (1) of Table III is

Table III
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 *SD*. Column (3) is identical to column (2) except the dependent variable subtracts off the natural logarithm of two-day admissions (days $t-1$ and $t-2$). The dependent variable in columns (4) to (6) subtracts off a rolling one-month (six-month, 12-month) average of the dependent variable. All independent variables are the same as in Table II. 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 *SD*	Minus Day $t-1$, $t-2$ Admits	Minus 1-Month Rolling Average	Minus 6-Month Rolling Average	Minus 12-Month Rolling Average
	(1)	(2)	(3)	(4)	(5)	(6)
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

–9 basis points ($t = –2.8$), nearly the average of the two coefficients in columns (4) and (5) of Table II, Panel B.

The second column of Table III scales *return* by a rolling one-year *SD* rather than the *SD* averaged over the entire sample. Observing that volatility varies over time, the 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 possibility, giving more weight to return realizations that occur in low-volatility regimes (say, 15%) versus those occurring in more volatile times (30%).

In this case, the estimated coefficient increases in both magnitude and statistical significance, from about 9 basis points to over 13 basis points ($t = 3.77$) measured over two days. This suggests that insofar as health outcomes reflect changes in subjective well-being, the effect of a given-sized market decline is more pronounced when investors are more "surprised." Although we do not present a specific model to microfound this effect, we note that it is consistent with investors evaluating the level or volatility of future consumption with

Table IV
Extreme Returns

The first two columns reproduce Table III, 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% level, respectively.

	Dependent Variable:			
	Log (Hospital Admits on Day t, $t \pm 1$)		Log (Hospital Charges on Day t, $t \pm 1$)	
	(1)	(2)	(3)	(4)
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

respect to a reference point, for example, the prospect theory of Kahneman and Tversky (1979).[11]

Because hospital admissions are a persistent variable and a rolling *SD* is also a persistent variable, the remaining columns consider 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. Column (3), (4), (5), (6) subtracts off a one-day (one-month, six-month, 12-month) moving average of the dependent variable. The results are largely the same. The coefficient on *return* ranges between –11.49 basis points and –14.04 basis points and is significant in each of these alternative specifications.

One question that arises immediately from the results in Tables II and III pertains to the linearity of the specification. In particular, one might expect extreme market declines to generate especially high stress levels, or sharp market increases to reduce baseline hospitalization rates. To investigate these possibilities, in the first two columns of Table IV we repeat the specification in

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

column (2) of Table III, but we allow *return* to enter through a series of dummy variables, one for each quintile in the empirical distribution. We find that only returns in the bottom quintile (i.e., large market declines) impact hospital admissions. When the market is in the bottom quintile of its distribution, hospitalizations increase by 0.31% over the next two days.

In the last two columns of Table IV we estimate the hospital costs associated with large stock market declines. In particular, we replicate the first two columns of Table IV after replacing hospital admits with *hospital charges* as the dependent variable.[12] We again find that only the bottom quintile of returns is significant. Given that two-day hospital charges in California average \$305 $\times$ 2 = \$610 million (Table I), and Table IV shows that bottom quintile returns associated with a 0.37% increase in hospital charges, this implies an annual cost of \$610 million $\times$ 0.37% $\times$ 252 (trading days) $\times$ 1/5 = \$114 million in 2011 dollars. Extrapolating to the United States based on population would increase this result by approximately an order of magnitude.

We urge caution, however, when attempting to infer the true economic magnitudes from these results. First, hospital care represents less than one-third of all healthcare costs in the United States.[13] But even this would be a conservative estimate of the health burden, given that 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 of \$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,[14] that is, ICD-9 codes in the range 290 to 319. These ailments include depression (296.2), panic disorder (300.01), alcohol dependence (303), and acute reaction to stress (308). Broadly speaking, these codes are related to mental health.

The first four columns of Table V show 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 *SD* decrease in the stock market corresponds to a 14 basis point increase in hospitalizations involving nonmental health codes, but a 21 basis point increase for those related to mental health. The results are more pronounced when we examine extreme returns (columns (2) and (4)). For nonmental health disorders, a bottom-quintile return corresponds to a 25 basis

[12] Charges are aggregated across all ICD-9 codes, as in Tables II and III. In subsequent analysis, we consider hospitalizations related to mental health conditions.

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

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

Table V

Hospital Admissions for Psychological Conditions

The dependent variable is the natural logarithm of new daily patients admitted to California hospitals between 1983 and 2011 on day t (columns (1) to (4)) and day $t+1$ (columns (5) to (8)). In columns (1), (2), (5), and (6), we exclude all patients admitted where the primary diagnosis is related to mental health, that is, 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 IV. Robust (White) standard errors are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.

	Dependent Variable: Log (Hospital Admits Day t)				Dependent Variable: Log (Hospital Admits Day $t \pm 1$)			
	Nonmental Disorders		Mental Disorders		Nonmental Disorders		Mental Disorders	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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

point spike in hospitalizations, whereas, for mental disorders, the coefficient is 58 basis points.

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 price declines yesterday continue to increase hospitalizations not related to mental health today. In sharp contrast, the lack of significance in columns (7) and (8) indicates that the effect of price declines on mental health-related hospitalizations concentrates entirely in the first day (columns (3) and (4)). One interpretation of this difference is that the initial manifestations of stress are mental, with more gradual effects on other organ systems as the consequences of stress accumulate.

III. What Can the Health-Wealth Relation Tell Us about Investor Preferences?

Characterizing investor 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, and 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 the types of events that appear most relevant for investors. In Section III.A below, we focus on timing, more specifically we examine the distinction between the utility effects of current versus expected consumption. In Section III.B, we focus on the types of events that may influence investor utility, for example, we address questions such as whether psychological distress is more sensitive to a decline in one's stock portfolio than, 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 suggests that the agent's current level of well-being is defined solely by current experience, be it a fine meal or a trip to the dentist's office. Second, it suggests that 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 impact the worker's utility to the extent that he or she adjusts today's consumption in response.

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

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

where g is the same generic function as in equation (2), and f is a function that translates expected future consumption, $E(C_{\tau>t})$, into 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 nonrecursive 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 the latter 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)) that have shown more promise in this regard.

One particularly relevant specification for our purposes is the model by Caplin and Leahy (2001), who explicitly incorporate 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.

Notably, despite the intuitive appeal of future events influencing an agent's well-being today, empirical evidence that expectations impact current utility is scarce. The reason is due in large part to the fact 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 this 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 pattern is consistent with three distinct explanations. 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 about being or becoming unemployed may have a direct utility effect. Indeed, the World Health Organization (2011) credits the recent economic crisis with causing devastating mental health effects.

By contrast, the high-frequency nature of our empirical tests makes it easier to 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 available to patients (the consumption channel), this is implausible at the daily frequency. In other words, while tightening an agent's lifetime budget constraint will optimally lead to a reduction in current and expected consumption (e.g., Lucas (1978)), that this could occur so drastically and quickly (i.e., within a few hours) to warrant hospitalization seems implausible. Instead, the immediacy of our main result, combined with it being particularly strong for conditions related to mental health, suggests that investors care about their consumption opportunities in the future beyond their impact on today's consumption.

To summarize, the results in Tables II–IV suggest two aspects of investor preferences that, outside experimental settings, may be difficult to observe.

First, expectations per se about future consumption are important for current utility. This follows from the instantaneous impact of stock market changes on both mental and physical health, and provides more direct support for the view that the standard expected utility framework is an inadequate description of investor preferences.

Second, the effect of expectations on current utility is asymmetric, mattering only for sharp decreases. One potential explanation for this is that the measure itself is asymmetric: going to the hospital is certainly bad news, but not going is not necessarily indicative of a positive shock to well-being. Another explanation may be 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 future consumption (i.e., $f()$ in equation (3) is also concave). This is consistent with reference-point models of utility, for example, Kahneman and Tversky (1979).

Before concluding, we note a number of caveats. Perhaps most importantly, we are taking seriously not only the idea that instantaneous utility exists (rather than acting as a workhorse for the expression of preferences), but also the idea that hospitalizations capture such well-being. Both of these assumptions could be challenged. For example, it is possible that hospitalizations reflect fluctuations in capitalized future utility (i.e., the value function), in which case our findings cannot be used to separate the utility impact of current and expected future consumption. Though outside our current scope, perhaps complementarities from the emerging neuroeconomics literature can help better make this distinction.

Second, we do not wish to imply that health outcomes encompass the entire spectrum of well-being, and we do not claim that our results allow for a full characterization of investor preferences. Moreover, while the immediacy of our results suggests a direct role for expectations, it is possible that some of our results could be driven by consumption-driven changes in behavior.[15] Yet, the role that expectations seems to play for current perceptions of well-being, particularly with respect to mental health, seems undeniable and provides an empirical foundation for utility formulations that explicitly take this into account.

B. Portfolio versus Nonportfolio Effects

The discussion above 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

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

market declines per se, or to the simultaneous arrival of economic news, perhaps about (potentially local) income or job growth. In the remainder of this section, we refer to these as *portfolio* and *nonportfolio* effects, respectively.[16] In this section, we attempt to distinguish between these two effects.

We first take a brute force approach to the problem. We start by identifying the 1,463 days that comprise the lowest 20% of returns over our sample period. Referring back to Table IV, 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 accompanies and/or causes the low average returns realized on these days, rather than the negative portfolio shock.

To assess this possibility, we read the NYT and WSJ the day following each of the 1,463 returns in the bottom quintile.[17] In each case, we determine whether a news event is identified as the reason for the decline, and if so, classify such events as follows: (1) macroannouncements (MA), (2) foreign conflicts (FCs) or terrorist attacks, (3) firm announcements (FAs), (4) prices in other markets (OPs), and (5) other events (OE).

A little more than half of the time (56%), no news event is provided. Although this may seem surprising, it is consistent with prior evidence. In particular, Cutler, Poterba, and Summers (1989), who read the NYT in an attempt to identify the reason for the 50 largest stock price movements in their sample, find several instances in which large stock movements were unaccompanied by fundamental news. In more recent work, Cornell (2013) repeats the analysis of Cutler, Poterba, and Summers (1989) using an updated sample and concludes that the mystery of unexplained price movements has deepened: "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 that we classify 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, an example of a story that we classify as attributing returns to a foreign conflict is:

[16] One might argue that this distinction is unimportant, given that it amounts to little more than capitalization, that is, whether investors care more about losing a dollar already earned in their portfolios versus one they expect to earn through labor income. On the other hand, because we are interested in addressing the feedback loop between sentiment and securities prices, we are interested in how prices, per se, influence the perceived well-being of investors.

[17] For the *WSJ*, we collect data from the "Abreast of the Market" column (e.g., Tetlock (2007), Dougal et al. (2012)), and for the *NYT*, we use the same sample as analyzed in Garcia (2013).

Table VI

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 IV, where the main independent variable is a binary variable that takes the value of one 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 III.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% level, respectively.

	Dependent Variable: Log (Hospital Admits on Day t, $t+1$)		
	(1)	(2)	(3)
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

> 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).

FCs are reported in 50 cases, with MAs accounting for another 203 event-days. Stories invoking OPs (e.g., oil or foreign exchange) were observed 115 times, while those involving FAs were observed 241 times. We classify 148 stories in the "other event" category. The latter represent instances in which we were not comfortable classifying the story as a nonevent, but we could not justify its inclusion in any of the other categories.

In Table VI, we rerun the specification shown in Table IV (with dummy variables for extreme returns) but exclude certain types of news. The first column repeats the benchmark results in Table IV for comparison. In the second column, we exclude the 50 days that involved a terrorist attack or FC. These events are arguably those that are most capable of independently impacting investor well-being, and in many cases are accompanied by extreme market declines. Accordingly, if their exclusion meaningfully alters our results, a portfolio-based explanation of our main results would become suspect. As can be seen, however, the coefficient is nearly identical to that in the prior column at 32 basis points

Table VII
Hospital Admits and Location

The dependent variable 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 (one-year) *SD*. *Non-California Return: Bottom Quintile* is a dummy variable that takes the value of one 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% level, respectively.

	Dependent Variable: Log (Hospital Admits on Day t, $t+1$)	
	(1)	(2)
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

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 VI is perhaps the best evidence that our main result is driven at least in part by the stock market per se rather than the news it reflects. In this column, the bottom quintile dummy turns on only for returns in the bottom quintile that are not associated with *any news event*. Examples 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 basis points ($t = 2.63$), indicating that the relation between hospitalizations and market downturns is nearly identical across news and nonnews days. To the extent that our classification adequately captures events capable of independently impacting investor well-being, the results in Table VI point to a portfolio-based interpretation of the main results shown in Tables III and IV.

Our second approach for distinguishing portfolio and nonportfolio effects is to exploit geographic differences across firm headquarters. The idea is that, for, say, California residents, fluctuations in the stock prices of California-based firms will contain, on the margin, more nonportfolio information (e.g., about job security) than fluctuations in the prices of firms not headquartered in California. For example, if Google misses earnings, this may cause its stock price to drop, which would adversely influence the portfolio of any investor in Google stock irrespective of where that investor lives. However, an investor living in

California—particularly in the Bay Area—would be exposed not only to this portfolio loss, but also to other losses for investors living in California, through real estate prices, the labor market, etc. Thus, a decline in Google would have both portfolio and nonportfolio effects, whereas a decline in a nonlocal firm such as ExxonMobil in Dallas should primarily have portfolio effects.

Table VII reports 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) reports results for the continuous return specification (similar to column (2) of Table III), while column (2) presents results for the dummy specification (similar to column (1) of Table IV). When continuous non-California returns alone are allowed to influence California hospital admissions (column (1)), we find a negative and significant coefficient of –9 basis points ($t = 3.59$). This is comparable to, although somewhat smaller than, the result in the benchmark specification in Table III. In the discrete specification in column (2), we find a coefficient of 35 ($t = 3.83$), which is slightly larger than in the benchmark specification (31 basis points) in Table IV. The finding that non-California returns put Californians in the hospital is in line with the existence of portfolio effects.

IV. Conclusion

In this paper, we provide evidence that, for a sample spanning roughly three decades, daily fluctuations in stock prices have an almost immediate impact on the physical health of investors, with a sharp price decline increasing hospitalization rates over the next two days. The effect is particularly strong for conditions related to mental health such as anxiety, suggesting that concerns over shocks to not only current but also to future consumption influence an investor's instantaneous perception of their well-being.

That we observe such a swift health response to stock prices—in most cases within two days of a price decline—has two implications. 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 such identification possible, and provides 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 implication 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 actually reduce welfare, particularly regarding events that ultimately have little bearing on outcomes (the recent barrage of media coverage of the "Fiscal Cliff" of 2012 comes to mind). Moreover, investors' distress may be compounded to the extent that the media amplifies the impact of fundamentals (see, for example, Dougal et al. (2012)). Accordingly, future research may 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 aggregate investor utility effects (particularly at the left tail), it potentially masks interesting interactions. 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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