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# Natural disasters and risk aversion

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ABSTRACT

The havoc brought by extreme weather events triggers well-documented adverse effects on human health, communities' resources and economic development. In this paper, we focus on the consequences of disasters on financial markets and infer the impact of major catastrophes on the risk-taking behavior of investors from U.S. municipal bond transactions. The findings strongly support the conjecture that natural disasters cause a statistically and economically significant increase in risk aversion at the local level. Although the change in investors' behavior appears to be temporary, this increase in risk aversion may dampen the stimulus effect of disaster financial assistance programs, slow the recovery phase and augment the perceived value of risk management programs and infrastructures.



## 1. Introduction

Research on natural catastrophes ('disasters' hereafter) has recently gained much traction due, in part, to the intensifying issue of global warming as well as to several large-scale events such as Hurricanes Katrina and Harvey that brought havoc to the affected communities. Such events caused tremendous damage and highlighted the necessity of studying the consequences of disasters.

In this paper, we focus on a specific consequence of disasters; namely, their impact on risk aversion. We define risk aversion as the tendency of investors to avoid undertaking risks and to choose less risky alternatives.[1] A variation in the propensity to take risks following disasters has major economic implications. Among others, (i) more risk averse individuals may take suboptimal investment decisions or refrain from opening new businesses or from exploring new technologies. In turn, this can dampen the stimulus effect of disaster financial assistance programs, slow the recovery phase and entail lower economic growth. (ii) Investors may require higher expected returns on assets for which regional risks cannot be properly diversified which could increase the financing cost for states and local governments and businesses, and also adversely

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impact the local housing market. (iii) Taxpayers and their agents in government might become more inclined to invest in risk management programs and structures as extreme weather events get more frequent and more severe.

Why would risk aversion changes follow major events? Although many authors remain agnostic about the cause, one frequently offered explanation is associated with an emotional story. Guiso et al. (2018) demonstrate that changes in the level of risk aversion in the wake of a global financial crisis better matches an emotional response story based on fear than explanations based on variations in beliefs, in wealth or in total habits. The theoretical framework of Loewenstein et al. (2001), i.e. the risk-as-feelings theory, that posits that "*responses to risky situations result in part from direct emotional influences*" (p. 270) is often cited to justify the linkage between emotion and the propensity to take risk. That emotions influence judgement and financial choices is also consistent with evidence presented by Lopes (1987), Lerner and Keltner (2000), Kuhnen and Knutson (2011), Wang and Young (2020), and others.

The academic literature on the relationship between disasters and risk aversion has grown in the last decade but arrives at mixed results. Indeed, Chuang and Schechter (2015) report a collection of studies suggesting a disaster-induced increase in risk aversion, but simultaneously note that an almost equal number of papers advocate for a neutral or negative impact of disasters on risk aversion. More recent studies are almost as evenly split between an increase (Goebel et al., 2015; Liebenehm et al., 2018) and a decrease (Brown et al., 2018; Kahsay and Osberghaus, 2018) effect on risk aversion from disasters. As for the cause of the effect, the importance of emotions is put forward by Smith (2008) who advocates that catastrophic events trigger lower optimism and higher risk aversion. Van den Berg et al. (2009) also allude to emotions to explain an increase in risk aversion while Eckel et al. (2009) and Hanaoka et al. (2015) suggest that the observed disaster-induced decrease in risk aversion may be due to an emotional response.

Our investigation distinguishes itself from the aforementioned studies in at least two respects. First, as investor preferences cannot be observed directly, researchers often rely either on self-reported questionnaire surveys, or on experiments involving synthetic environments with often incentivized subjects to assess risk aversion. Instead, we estimate risk aversion through economic modeling with risk aversion embedded as a structural parameter that can be inferred from observed financial asset prices. Each approach clearly has its own advantages and limitations. Our approach suffers from the fact that all models are simplified reflections of reality. Furthermore, the risk aversion parameter of our model combines information on risk preferences with information on beliefs about the likelihood and the severity of future disasters. We lessen concerns about measurement error by investigating the duration of the effect of disasters on our parameter. We surmise that if extreme weather events bring new information about future disasters to market participants and affect investors' beliefs, we should observe a long lasting, if not permanent, shift in the model parameter. However, if disasters affect investors' risk preferences *per se*, the emotional-based transmission channel allows for a short-term effect. The advantages of our approach are that it makes available for an examination of the time-variation in risk aversion, and allows us to assess the average effect of disasters on risk aversion using a relatively large panel of events and localities. The use of such a panel averages out the effect of most of the peculiar characteristics of disasters and also alleviates the possibility that results are biased by geographical factors such as culture (Brown et al., 2018) or rurality (Liebenehm et al., 2018).

Second, we study risk aversion at an aggregate level rather than at the individual or household level. This perspective allows us to comment on whether or not the effects of disasters on risk aversion are widespread enough to impact financial markets and on the signals they provide for capital allocation. While Kahsay and Osberghaus (2018) find that floods only affect risk preferences of people directly impacted by disasters, Chen et al. (2012) show that only a small number of formerly optimistic investors becoming pessimistic can substantially affect asset prices by increasing risk premiums. Therefore, whether or not the pricing of financial assets is consistent with a variation in risk aversion instilled by natural disasters remains an elusive empirical question. This research question appears important especially given the foreseen increase in the frequency and intensity of extreme weather events that lead to critical public issues. To the best of our knowledge, we are the first to study the impacts of disasters on risk aversion from such a financial market perspective.

The empirical strategy we follow rests on one fundamental premise: we assume that disasters, through the emotion channel, essentially cause small temporary deviations in the long-term level of risk aversion. We employ a well-known type of asset pricing model, the consumption-based capital asset pricing model (CCAPM) to assess the relationship between financial asset prices and consumption growth. In the model, this relationship is explained through a risk aversion parameter, which allows us to observe if the patterns in the relationship are consistent with disasters having a systematic effect on risk aversion. The conjecture of a near-constant level of risk aversion is consistent with Schildberg-Hörisch (2018) who uses a framework where risk aversion follows a distribution "*with a mean that is significantly but less than perfectly stable*" (p.136). It is also in line with Kamstra et al. (2014) who modulate risk aversion according to the time of the year to study the effect of seasonal affective disorder.

However, investigating reactions to disasters using an economic model is not a straightforward exercise. One may rightly argue that extreme weather events wreak havoc locally (West and Lenze, 1994) and that their upmost consequences are usually narrowed to a relatively small share of the population. Thus, it appears unlikely that disasters trigger a strong emotional reaction to a large enough number of individuals such that the risk preference of the average investor in the U.S. is significantly affected. Accordingly, we implement our empirical examination to the regional level to ensure that the risk aversion parameter reflects the risk preferences of local investors. In other words, while the large majority of studies using a CCAPM fit the model's risk aversion parameter on the returns of stock market indices, we need to identify a market where assets are prominently traded regionally by local investors.

One financial market where payoffs are well defined and trading is segmented along clear-cut geographic limits is the municipal bond market. Previous literature suggests that the municipal bond market is geographically segmented at the state-level due to asymmetric tax exemptions (Pirinsky and Wang, 2011), to local home bias (Greer and Denison, 2014), to differences in relative security supplies (Hendershott and Kidwell, 1978; Kidwell et al., 1987) and to disparities in information costs (Feroz and Wilson, 1992). Furthermore, Ang et al. (2010) maintain that local retail investors dominate the trading of tax-exempt municipal bonds.

Although the majority of asset pricing studies have used stock market indices as test assets, we maintain that inferring investor preferences from municipal bonds has some other non-negligible advantages. First, Vissing-Jørgensen and Attanasio (2003) and others offer strong evidence that asset pricing models should be tested using after-tax returns. Unlike most other categories of assets, municipal bonds provide a clear and direct view of after-tax returns. Second, since we cannot observe the true expectations of investors, empirical tests of asset pricing models assume that ex-post realized returns are a good proxy for the ex-ante expectations of the next-period returns (e.g. Donaldson and Kamstra, 1996). We argue that a larger proportion of the returns from municipal bonds compared to most other financial assets is expected given fairly assured coupon payments, relatively low incidence of defaults and the finding that default risk accounts for more than three-quarters of an average bond spread (Schwert, 2017). Regarding default risk, it is worth noting that Kriz (2004) establishes that municipal bonds are perceived as risky assets by investors so that risk aversion affects the pricing of these assets. Finally, Campbell (1980) reports evidence consistent with the belief that the municipal bond market is efficient, and Fischer (1983) finds that yields quickly reflect new information even for infrequently traded bonds.

In addition to asset prices, estimating a CCAPM requires information on consumption growth. Common measures of consumption growth used in asset pricing studies include personal consumption expenditures (PCE) and consumption of non-durable goods and services (NDS) reported by the Bureau of Economic Analysis of the U.S. Department of Commerce. However, state-level data on PCE and NDS are only available at an annual frequency, which limits our ability to run an event study on the impact of disasters. We solve this issue by following Da and Yun (2010) by using the growth of monthly electricity usage. Not only does electricity usage satisfy our needs in terms of consumption data, but it is also successfully employed in existing asset pricing papers. Indeed, empirical tests of the convention CCAPM often reject the model as it fails to simultaneously explain the price of the test assets and the rate of treasury bills (Hansen and Singleton, 1983). However, Da and Yun (2010) find strong supporting evidence for the CCAPM at both the aggregate and the state level using electricity usage growth as their measure of consumption (also, see Da et al. (2017), for this measure's ability to predict market returns).

We proceed with our empirical analysis and generate our main results using two distinct approaches. First, we account for geographic investor heterogeneity and estimate a model where investors differ from state-to-state with respect to their level of consumption, but retain the same average level of risk aversion throughout the country. To do so, we structure the CCAPM drawing on the work of Jacobs et al. (2013) with the distinctive feature that each state-level consumption series must be matched against the municipal bond index of the corresponding state. To examine the impact of disasters, we split the risk aversion parameter into two components: a time- and region-invariant coefficient that expresses the mean level of risk aversion of U.S. investors, and a second coefficient proportional to the amount of disaster-related damage. This second component varies over time and across regions and reflects the mean systematic effect of disasters on risk aversion.

Second, we assume that the municipal bond market is perfectly segmented at the state-level so that the pool of investors completely differs from state to state. We then separately estimate the conventional canonical CCAPM of Hansen and Singleton (1983) in each state to obtain one risk aversion coefficient per state. We rationalize our assumption that risk aversion varies across states by noting that several key components of the investors' environment, such as the laws or regulations and most of the welfare policies that influence precautionary saving and income risk policy (Bird and Hagstrom, 1999), are not only shared by investors at the state-level, but differ significantly from state to state. Regional differences in risk aversion imply that fiscal incentives for private investment in risk management, housing, small businesses, etc., can be expected to differ in their regional effectiveness. This time, we retain a single time- and region-invariant risk aversion coefficient in the conventional CCAPM and instead examine the model's residuals to find evidence of disaster-related variations in risk aversion. We posit that if disasters are to cause a variation in risk aversion, then disaster-related damage should be significantly and systematically correlated with the model's residuals. We run a regression analysis on the CCAPM's residuals to test our conjecture.

We aim to show the robustness of our results by using two approaches involving differing assumptions and structures for the CCAPM and distinct measurable metrics for the variation in risk aversion. However, we also implement additional robustness tests to validate our conclusions. Among other things, we examine how alternative ways to measure disaster losses affect the main results, how the results from high-risk states compare to the base case, and how expectations about disaster losses affect our conclusions. The results for all of the empirical tests consistently suggest that disasters cause a momentary increase in risk aversion.

The rest of the paper is organized as follows. Section 2 describes the theoretical foundations of the CCAPM and provides a brief review of the literature. Section 3 presents the data. Section 4 outlines the methodology for the empirical event study analysis. Section 5 displays and discusses the results from the empirical analysis. Section 6 concludes.

## 2. Theoretical background

Over approximately the last 50 years, the dominant paradigm in the field of economic decision making under uncertainty has been the expected utility (EU) theory. EU postulates that an investor's decision process follows a rational assessment of the expected outcomes of available alternatives. Derived from the EU theory, the fundamental asset pricing equation states that prices "*should equal expected discounted value of the asset's payoff, using the investor's marginal utility to discount the payoff*" (Cochrane, 2005 p.3). Given that an investor's true utility is unobservable, the asset pricing literature provides a large variety of mathematical representations for investors' utility functions and often expresses utility as a function of consumption. Typically, the utility functions are increasing in consumption given investor's non-satiation and are usually concave given that investors are assumed to be risk averse, at least for large stakes (Rabin, 2000). The fundamental asset pricing equation can be written as:

$$\mathrm{P}_t = E\left[\beta\frac{U'(C_{t+1})}{U'(C_t)}\mathrm{X}_{\mathrm{t+1}}\middle|\Omega_{\mathrm{t}}\right] \tag{1}$$

where $\mathrm{P}_t$ is the price of an asset at time $t$, $\beta$ is the subjective discount factor depicting investor impatience, and $U'(\cdot)$ is an investor's marginal utility defined over the current value of consumption $C_t$ and future values of consumption $C_{t+1}$. $\mathrm{X}_{\mathrm{t+1}}$ is the payoff of the asset and $\Omega_{\mathrm{t}}$ is the information set that is known to the investor when making the investment decision. Given the uncertainty of future consumption and future asset payoffs, beliefs about the prospective states of the world can implicitly be interpreted as weights for the expectation operator $E[\cdot]$.

In this paper, risk preferences arise from Eq. (1) in the form of a (Arrow-Pratt) coefficient of relative risk aversion ('risk aversion' hereafter). The coefficient is measured formally as the percentage change in marginal utility from the test asset payoffs divided by one percentage change in the payoffs (investor's wealth). A relative measure (dividing variation in marginal utility by variation in wealth) is often preferred by economists over an absolute measure (variation in marginal utility) of risk aversion, as the earlier measure is unit-free (see Eeckhoudt et al. (2011) for a thorough definition and discussion of risk measures in the context of the EU). However, estimated values of risk aversion are sensitive to how consumption and asset payoffs are measured. This sensitivity implies that comparisons of risk aversion estimates reported in the literature can be hazardous (Meyer and Meyer, 2005). Among other things, the use of after-tax municipal bond returns may lead to lower risk aversion estimates than most asset pricing analysis implemented using before-tax stock returns. This comparability issue by no means invalidates the conclusions we report later in Section 5 as both our base case and our post-disasters empirical estimates are obtained concurrently using the exact same data. Yet, the sensitivity to how asset payoffs are calculated explains our focus on *variations* in estimated risk aversion rather than on the point estimates.

Empirical implementations of the CCAPM often follow Hansen and Singleton (1983) and assume power utility. It is also common to divide both sides of Eq. (1) by prices so as to work directly with asset returns. As observable data on historical returns and on consumption growth are used in most empirical analyses, researchers typically give equal weight to each period of data. Following these additional assumptions, the conventional CCAPM can be written as:

$$1 = \mathrm{E}\left[\beta\frac{\mathrm{C_{t+1}}}{\mathrm{C_t}}^{-\gamma}\mathrm{R_{t+1}}\ |\Omega_{\mathrm{t}}\right] \tag{2}$$

where $m_t = \beta\frac{\mathrm{C_{t+1}}}{\mathrm{C_t}}^{-\gamma}$ is referred to as the stochastic discount factor (SDF), $\frac{\mathrm{C_{t+1}}}{\mathrm{C_t}}$ corresponds to the growth in consumption, $\gamma$ stands for the risk aversion coefficient, and $R_{t+1}$ is the gross asset return.

Optimal investment decisions entail a trade-off between the (known) loss in utility associated with the purchase of a unit of an asset that reduces consumption at time $t$ and the (uncertain) increase in utility related to the additional payoff of the asset that will augment consumption at time $t + 1$. As shown in Eq. (2), risk preferences enter Eq. (1) in the form of a constant risk aversion parameter embedded in the SDF. In concordance with basic economic intuition, an increase in the risk aversion parameter lowers the utility of the uncertain future asset payoff. In turn, this decreases the optimal number of assets that an investor should buy and the lower demand leads to a drop in the asset price.

From our empirical analysis standpoint, the exercise is one of model fitting where historical data on asset returns and on consumption growth are used to estimate the values of the impatience and risk aversion parameters such that departures from Eq. (2) are minimal. Several studies employ Eq. (2) to try to explain asset prices, but the data used in many of them leads to the rejection of the model (Campbell and Cochrane, 2000).

In response to the rejection of the conventional CCAPM, researchers obtain some success by using alternative utility functions (Campbell and Cochrane, 1999; Epstein and Zin, 1991), by developing new measures of consumption (Da and Yun, 2010; Savov, 2011), or by accounting for the heterogeneity of investors (Brav et al., 2002; Constantinides and Duffie, 1996; Sarkissian, 2003). The latter two lines of research are of particular interest for this paper. Our analysis relies on a relatively novel measure of consumption based on electricity usage, and we exploit regional consumption and returns data to create state-level SDF in order to account for differences between investors based on geography.

## 3. Data

In this section, we outline the three main datasets containing information on natural disasters, state-level consumption and municipal bond returns, respectively. Our analysis covers the 2005 to 2017 period and extends over the 50 states (but

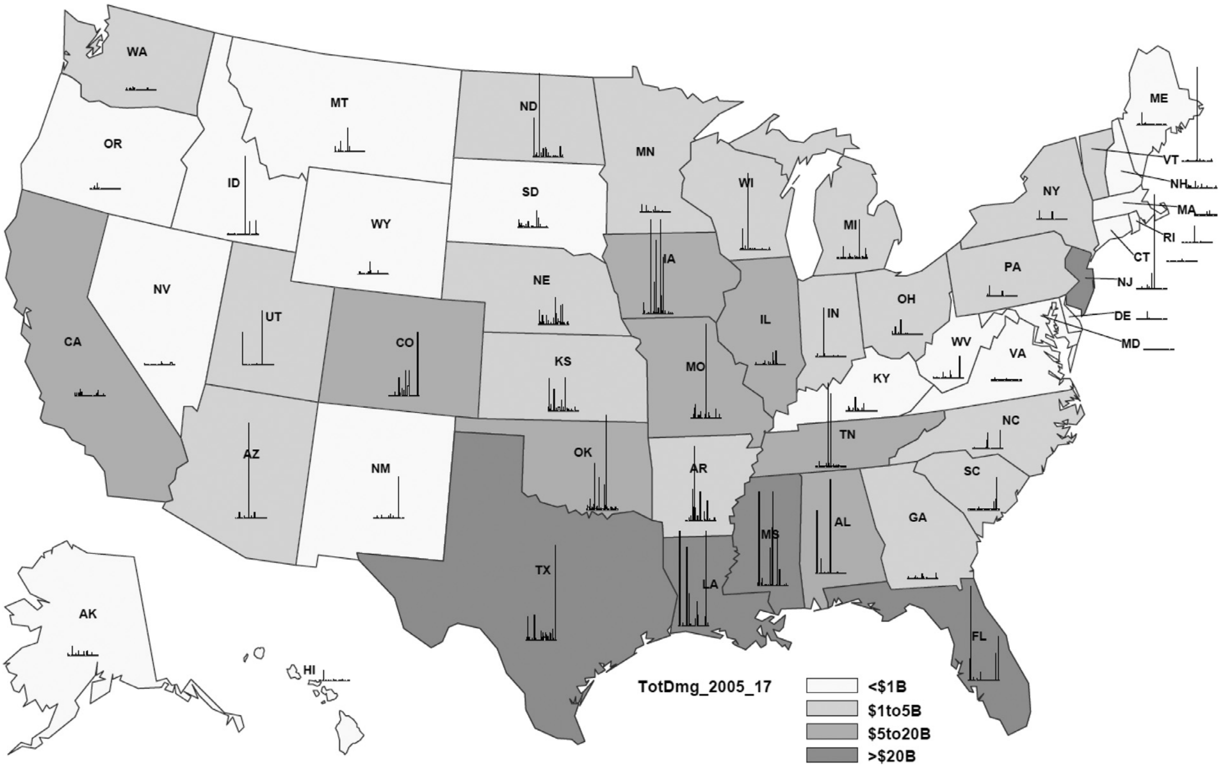


**Fig. 1.** Dispersion of disaster-related losses expressed as a fraction of state GDP (DIS) over time and across states.

excludes the District of Columbia due to data availability). All data are sampled at a monthly interval in order to maximize the power of the tests without being unduly affected by microstructure noises in the case of returns.

### 3.1. Extreme weather events

We obtain aggregate data on the monetary value of losses owing to natural disasters by month and state between 1996 and 2017 from SHELDUS, the Spatial Hazard Events and Losses Database for the United States (CEMHS, 2018). SHELDUS is an often cited database that covers natural hazards such as thunderstorms, hurricanes, floods, wildfires, or tornados. It contains information on the date of an event, the affected location and the associated losses. The loss data encompass damage to properties and to crops but exclude economic losses, environmental damage and other indirect hazard-related costs.[2] As this study examines the effect of disasters over several years and over a relatively large geography, it appears desirable to normalize disaster losses so that damages are expressed in terms of losses relative to what can potentially be destroyed. To this end, we follow the suggestion of Neumayer and Barthel (2011) and express disaster losses as a fraction of wealth, using the previous period's state-level GDP from the U.S. Bureau of Economic Analysis as the proxy for wealth.[3]

Summary statistics between 2005 and 2017 reveal that the monthly loss expressed as a fraction of state-level GDP (DIS) averaged 0.018 percent, but exhibits large variations both across states and over time. Standard errors of the pooled monthly disaster losses series is 0.48 percent. DIS displays moderate cross-sectional correlations. Pairwise rank correlations average 0.19 and vary between −0.18 (between North Dakota and Washington) and 0.67 (between Louisiana and Mississippi). The somewhat low correlations reflect the local nature of most disasters.

Fig. 1 displays the geographic and temporal dispersion of disaster-related damage where losses exceeding one percent of GDP are winsorized for ease of illustration. The heat map informs on the dispersion of cumulative direct losses (in constant billions of 2017 dollars) related to disasters that occur between 2005 and 2017. Bar charts show the value of DIS over time by state. Table 1 lists the 15 events with a value of DIS in excess of one percent.

[2] See Gall et al. (2009) for a general discussion of limitations and potential biases associated with loss data.

[3] Note that we reach similar conclusions using alternative normalization schemes such as expressing constant dollar disaster losses on a per capita basis. Results also remain materially unchanged if we use the natural logarithm of total disaster losses.

**Table 1**
Largest disasters in terms of losses as a fraction of state-GDP.
Table I lists the 15 state-month observations with disaster-related direct losses expressed as a fraction of the previous-period's state-level GDP in excess of one percent between 2005 and 2017. Direct losses come from SHELDUS and consist of the sum of crop- and property-losses estimates. State-level GDP comes from the U.S. Bureau of Economic Analysis and is available at a quarterly frequency. Details about the spatial and temporal distribution of monthly disaster-related losses arising from smaller events are available in Fig. 1.

| Date | State | Informal event name | Total losses($M 2017) | Per-capita losses($ 2017) | Total losses / State GDP (%) |
|---|---|---|---|---|---|
| 2005–08 | Mississippi | Hurricane Katrina | 33,203 | 11,426 | 32.98 |
| 2005–08 | Louisiana | Hurricane Katrina | 61,000 | 13,329 | 24.58 |
| 2008–06 | Iowa | Iowa "Katrina" Flood | 9302 | 3083 | 5.90 |
| 2017–08 | Texas | Hurricane Harvey | 90,458 | 3196 | 5.46 |
| 2011–08 | Vermont | Hurricane Irene | 1475 | 2356 | 4.81 |
| 2012–10 | New jersey | Hurricane Sandy | 26,717 | 3014 | 4.76 |
| 2016–08 | Louisiana | Louisiana Floods | 9259 | 1985 | 3.94 |
| 2011–04 | Alabama | Super Tornado Outbreak | 4827 | 1009 | 2.45 |
| 2005–09 | Louisiana | Hurricane Rita | 5602 | 1224 | 2.29 |
| 2012–07 | Iowa | Severe Drought | 2588 | 842 | 1.51 |
| 2005–10 | Florida | Hurricane Wilma | 12,992 | 728 | 1.47 |
| 2011–05 | Missouri | Joplin Tornado | 3436 | 574 | 1.21 |
| 2013–05 | Oklahoma | Moore Tornado | 2227 | 581 | 1.16 |
| 2010–10 | Arizona | Phoenix-area Hailstorm | 3185 | 499 | 1.13 |
| 2011–05 | Mississippi | Mississippi River Floods | 1118 | 377 | 1.06 |

### 3.2. State-level consumption

The search for a suitable proxy for local consumption is challenging as official state level statistics for personal consumption expenditures (PCE) or for consumption of non-durable goods and services (NDS) are only available at an annual frequency, which limits our ability to run an event study on relatively short-term events such as natural disasters. Recent publications employ data on electricity consumption as a way to overcome the issues. Da et al. (2015) use residential electricity usage to proxy for the service flow from households and show that electricity usage significantly helps to explain stock returns. Most relevant to this study, Da and Yun (2010) use total electricity usage as a measure of consumption in the context of the CCAPM. Unlike previous studies, they find strong supporting evidence for the CCAPM at both the aggregate and the state level.

Often cited advantages of using electricity consumption over traditional measures of personal consumption in asset pricing are that electricity consumption is (i) gauged very precisely, (ii) measured with no delay, and (iii) consumed over the life of the product (Do et al., 2016). In the U.S., data on electricity consumption is available monthly by state and by user type through the Electric Power Industry Report of the U.S. Energy Information Administration. However, the absence of electricity usage data on small areas prevents us from examining the relationship between natural disasters and risk aversion at the intra-state level.

The construction of our state-level electricity consumption growth series (CG) is based on residential electricity usage. It is calculated as the monthly electricity consumption growth made orthogonal to weather variations and population changes. The step-by-step construction mirrors the approach of Da and Yun (2010) and details are described in greater length in the online supplementary appendix.

Summary statistics indicate that annualized consumption growth averages 1.79 percent between 2005 and 2017. This average is a bit lower, but remains of similar magnitude, than the average annualized growth of the national real PCE over the same period (1.99 percent). However, the standard deviation of CG is much higher than that of the state-level PCE (10.96 percent vs. 3.43%). Such a large difference is consistent with other studies using state-level consumption measures (Da and Yun, 2010; Jacobs et al., 2013) and is likely to improve the performance of the conventional CCAPM relative to estimations based on traditional consumption measures. Pairwise rank correlations between state-level CG series average 0.57 and vary from 0.05 (between Louisiana and North Dakota) and 0.93 (between Arkansas and Mississippi). The relatively high correlations between the monthly series reflect the existence of common mechanisms – credits, savings and capital markets, taxes and transfers, labor force mobility, etc. (Parsley and Popper, 2018) that help smooth consumption.

Fig. 2 displays the geographic and temporal dispersion of electricity consumption growth. The heat map informs on the dispersion of average annualized growth in electricity consumption between 2005 and 2017. The state-level line chart shows the value of CG over time.

### 3.3. Municipal bond returns

Municipal bonds (munis) are financial securities issued by states, cities, counties, school districts, special purpose districts or other local governments. They are mainly used to finance capital expenditures or to redeem outstanding maturing bonds.

We obtain a comprehensive dataset of transactions of munis between January 5th, 2005 and December 31th, 2017 from the Municipal Securities Rulemaking Board (MSRB) transaction database. The MSRB dataset gives basic descriptive information on bonds such as the CUSIP identification number, the issuance date, the maturity date, the coupon rate, as well as the

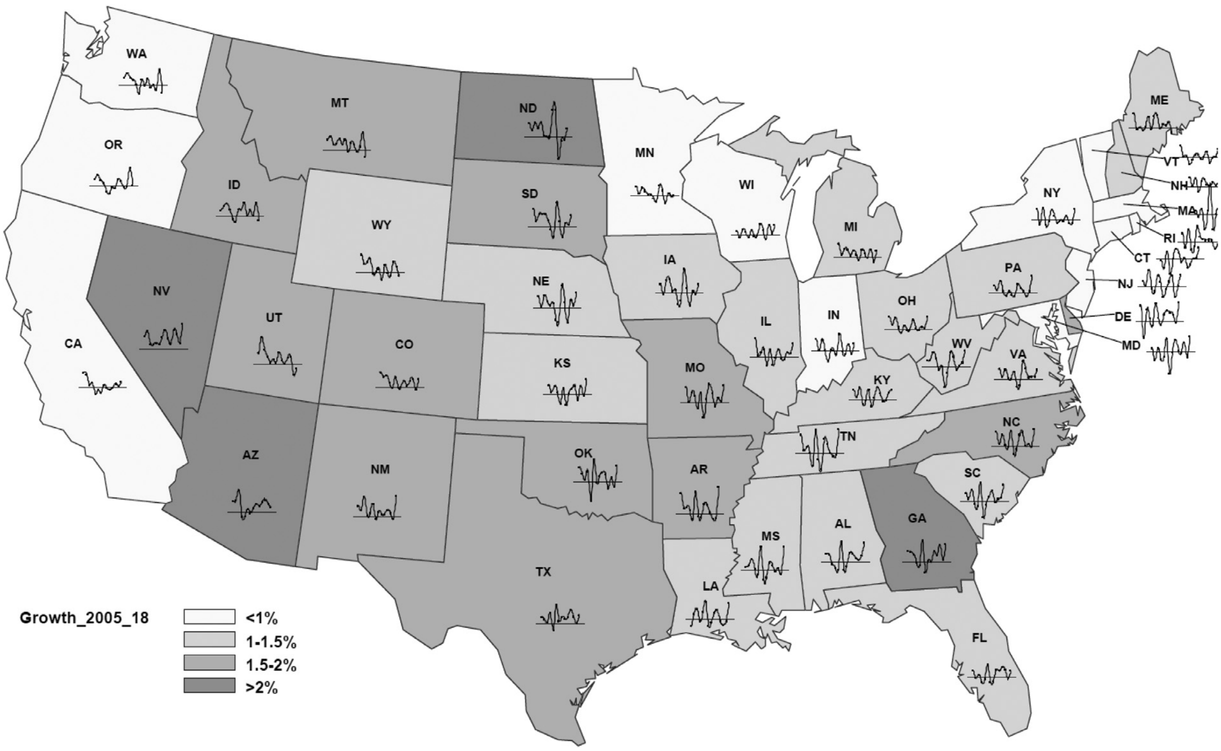


**Fig. 2.** Dispersion of electricity consumption growth (CG) over time and across states.

date, time, quantity and price of each bond transaction. The dataset also discloses a trade-type indicator that tells whether the trade is initiated by a buyer, a seller or a bond dealer. The dataset lists about 123.03 million transactions on 2.76 million unique CUSIP from 57,419 distinct issuers.[4] We extract information on the state where each issuer is located and the tax status of each security from Refinitiv Eikon and Bloomberg. We exclude from our sample issuers that are spread across several states, bonds issued by American territories, taxable bonds and bonds with missing or time-varying coupon rates to ensure that the accurate calculation of accrued interest is possible.

The municipal bond market is characterized by a high number of infrequently traded securities marketed by many relatively small issuers. Infrequent trading means that investors cannot easily assess the returns of individual bonds due to the absence of observable market prices at several points in time. Also, munis trade on a decentralized broker-dealer market where buyers and sellers execute orders separately and independently through broker-dealers. Consequently, individual transactions listed in the MSRB dataset give information on one of the two legs of a roundtrip transaction. Thus, observable trade prices inform on the reservation price of the buyer or seller instead of on market prices. We proceed in three steps to address these issues. First, we identify the two legs (buyer and seller) of the same roundtrip transaction using the approach developed and described by Green et al. (2007). That approach consists in matching buyer-(seller)-initiated transactions with subsequent bond sells (buys) equal in par value. We ignore the observations that cannot be associated with the legs of a round-trip transaction and require traded bonds to have a time-to-maturity of at least one year. Second, we calculate the mid-price of each round-trip transaction and assume that the mid-price is an adequate proxy for market prices. The exclusion criteria and the construction of round-trip transactions greatly reduces the number of observations to 9.40 million on 1.05 million unique CUSIP sold by 36,433 distinct issuers. Third, we employ the S&P/Case-Shiller Home price index methodology of Shiller (1991) to construct state-level monthly indices from individual transaction prices adjusted for accrued interest and coupon payments. Last, we calculate monthly muni returns (RET) from the repeated-sales indices. More details on the construction of the municipal bond repeated-sales indices are available in our online supplementary appendix.[5]

RET averages 0.35% (4.74 percent annualized) with a standard deviation of 0.83%. Monthly returns range from −0.64 percent (California, October 2008) to 7.00% (Mississippi, January 2009). Pairwise rank correlations between state-level RET series average 0.73 and vary between 0.21 (between Mississippi and Wyoming) and 0.96 (between New York and Penn-

[4] In this paper, we refer to securities with separate CUSIP numbers as "CUSIP' or "bonds" and the collections of bonds with a range of maturities from the same issuer and marketed simultaneously as "series".

[5] Note that we also considered using the S&P municipal bond indices as test assets. However, about half of the states have indexes that started in 2010, which would have shrunk the sample size considerably.

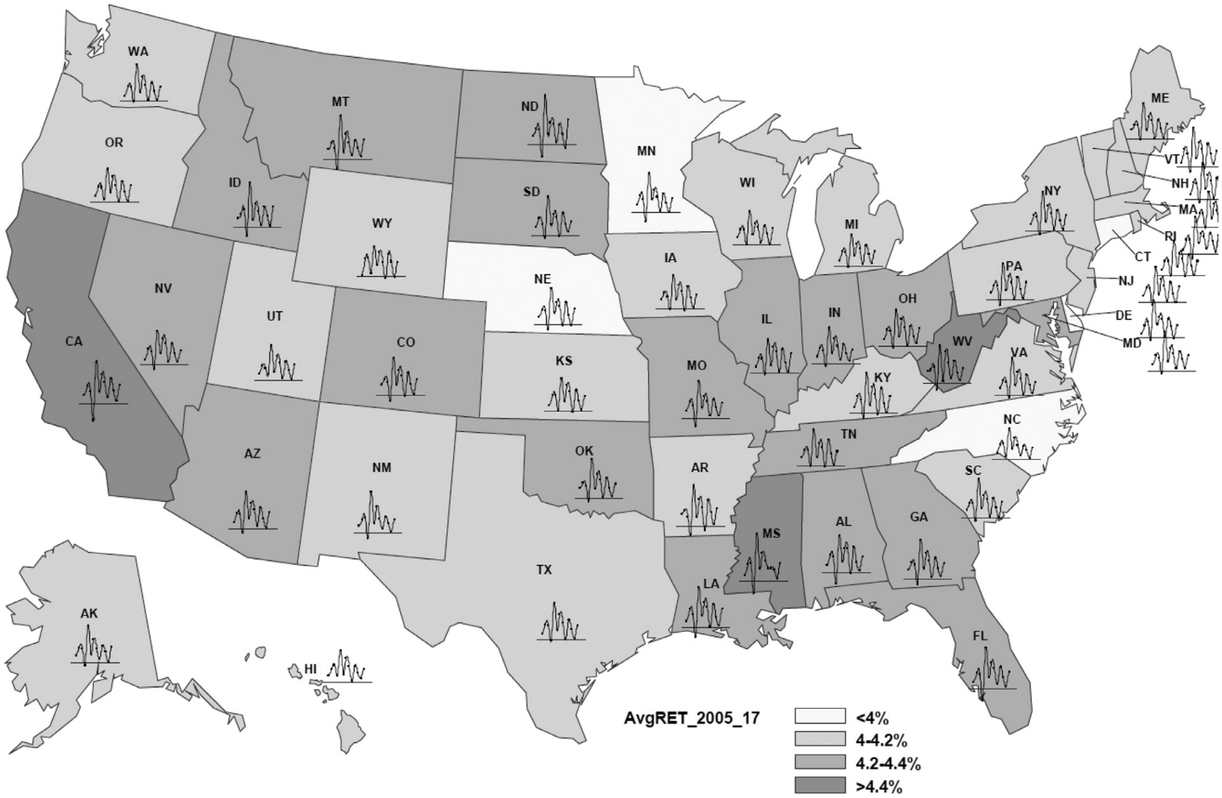


**Fig. 3.** Dispersion of monthly MUNI returns (RET) over time and across states.

sylvania). The relatively high average correlation across states is not much of a surprise given that the prices of municipal bonds arguably depend on common factors such as the level of interest rates. Fig. 3 displays the geographic and temporal dispersion of RET. The heat map informs on the dispersion of annualized cumulative muni returns between 2005 and 2017. The state-level line chart shows the value of RET over time.

## 4. Methodology

Since we allow investors to differ from state-to-state with respect to their level of consumption in our estimation approaches, we obtain state-level SDF. This is consistent with the quasi-consensus that munis trade in markets segmented around state lines. The state-level SDF in our model is matched against the returns of the municipal bond index of the corresponding state. In line with many influential papers in the asset pricing literature (e.g. Breeden and Litzenberger, 1978; Hansen and Singleton, 1983; Mehra and Prescott, 1985), we assume that investors exhibit time-separable constant relative risk aversion (CRRA). For simplicity, we focus on an unconditional version of the CCAPM. That is, we consider that the information set contains only a constant equal to one. As for the risk aversion parameter, many influential asset pricing papers dealing with investor heterogeneity retain the assumption that investors share similar risk aversion (Brav et al., 2002; Constantinides and Duffie, 1996; Jacobs et al., 2013).[6] However, if disasters cause a long-term shift in risk aversion, then disasters by themselves could explain differences in risk aversion across regions. Assuming that risk aversion is the same in all states reduces the number of parameters in the model and may lead to a more stable estimate of risk aversion. On the other hand, constraining risk aversion to be the same everywhere may obscure the long-term impact of disasters and thus bias the results. This leads us to develop two distinct estimation approaches, a first one where we assume a single rate of risk aversion for all U.S. investors and a second one where we let risk aversion vary over states.

### *4.1. Estimation approach with a single rate of risk aversion*

In our first approach, we modify Eq. (2) and pair state-level SDFs with the excess returns of the state-level muni indices over the risk-free rate. As noted previously, we also split the risk aversion coefficient into two components: a time- and

[6] Other papers in the asset pricing literature develop models where investors differ in their risk aversion (Chan and Kogan, 2002; Wang, 1996).

region-invariant coefficient $\gamma^{US}$ that expresses the mean level of risk aversion of U.S. investors, and a second coefficient $\gamma^{DIS}$ proportional to the amount of disaster-related damage. We obtain the following equation:

$$0 = E\left[\beta \frac{C_{j,t}}{C_{j,t-1}}^{-(\gamma^{US}+\gamma^{DIS}DIS_{j,t-k})}\left(R_{j,t} - R_{f,t}\right)\right], \; j = 1, \ldots, J, \; t = 1, \ldots., T \tag{3}$$

where $R_{f,\,t}$ is the risk-free rate proxied by after-tax returns on the 3-month treasury bills[7] and $DIS_{j,t-k}$ is the total amount of disaster-related damage expressed as a fraction of state-level GDP in state $j$ in the $k^{th}$ previous month. Note that the two components of the risk aversion parameters $\gamma^{US}$ and $\gamma^{DIS}$ have no subscript, as they are assumed common to all dates and states.

We use a generalized method of moments (GMM) procedure to estimate the CCAPM's parameters. We construct one moment condition per state j so that:

$$u_T^j\left(\beta, \gamma^{US}, \gamma^{DIS}\right) = \frac{1}{T}\sum_{t=1}^{T} \beta \frac{C_{j,t}}{C_{j,t-1}}^{-(\gamma^{US}+\gamma^{DIS}DIS_{j,t-k})}\left(R_{j,t} - R_{f,t}\right) \tag{4}$$

where $u_T^j(\beta, \gamma^{US}, \gamma^{DIS})$ is the mean residual in state $j$.

However note that the impatience parameter $\beta$ is not well defined in this setup and cannot be estimated with these moment conditions. Indeed, mean residuals reach zero in all periods and states when $\beta = 0$. Many authors simply assume $\beta = 1$, implying that investors are indifferent between current and one period ahead consumption (e.g. Brav et al., 2002). While the level of the impatience parameter has a scaling effect on the residuals, it does not affect the estimated value of the risk aversion parameter. If, as expected, investors prefer consuming now than in the future, then the impatience parameter should be slightly less than one. In this first approach, we estimate the impatience parameter by adding a 51st moment condition to our system:

$$u_T^{r_f}\left(\beta, \gamma^{US}, \gamma^{DIS}\right) = \frac{1}{T \times J}\sum_{t=1}^{T}\sum_{j=1}^{J} \beta \frac{C_{j,t}}{C_{j,t-1}}^{-(\gamma^{US}+\gamma^{DIS}DIS_{j,t-k})} R_{f,t} - 1 \tag{5}$$

The SDF of this last moment condition ($\frac{1}{J}\sum_{j=1}^{J} \beta \frac{C_{j,t}}{C_{j,t-1}}^{-(\gamma^{US}+\gamma^{DIS}DIS_{j,t-k})}$) is like the incomplete-market SDF of Jacobs et al. (2013). The inclusion of investors' consumption patterns from all states reflects the fact that treasury bills trade in a non-segmented market.

Putting all together, the GMM estimation seeks to minimize:

$$obj = \min_{\beta,\gamma^{US},\gamma^{DIS}} \left[u_T\left(\beta, \gamma^{US}, \gamma^{DIS}\right)' W \; u_T\left(\beta, \gamma^{US}, \gamma^{DIS}\right)\right] \tag{6}$$

where $u_T$ is the vector containing the 51 moment conditions and W represents the weighting matrix. We use the second-moment matrix of returns advocated by Hansen and Jagannathan (1997) as the weighting matrix W. The second-moment matrix minimises the distance between the estimated SDF and the set of valid SDFs arising from economic theory. Thus, it is an interesting measure of economic fit to use in our context.

### 4.2. Estimation approach with one rate of risk aversion per state

In our second estimation approach, we retain the canonical CCAPM of Hansen and Singleton (1983) but estimate the model at the state-level instead of at the aggregate U.S. level. This means that we assume that the muni markets are completely segmented by state so that a distinct representative investor with its own risk preference exists in each state. In this setup, we drop the risk-free return from the analysis as out-of-state investors may drive the price of treasury bills. Accordingly, we include only one test asset per state in our model. As we need at least as many moment conditions as parameters to obtain a unique solution, we include only one parameter in our estimation and thus assume that $\beta = 1$. We obtain the following equation for each state j:

$$1 = E\left[\frac{C_{j,t}}{C_{j,t-1}}^{-(\gamma_j)} R_{j,t}\right], \; j = 1, \ldots, J, \; t = 1, \ldots T \tag{7}$$

Iteratively for each state, we estimate $\gamma_j$ by minimizing departures to Eq. (7) and then investigate the impact of disasters on risk aversion by running a panel analysis on the model's pricing errors.

As we fit our model on 13 years of state-level data covering the 50 states, this results in a panel of 50 time-series of pricing errors containing 156 monthly observations. The identification strategy for a disaster-driven increase in risk aversion

[7] Treasury bills are exempt from income tax at the state level. We use the annual maximum state income tax rates from NBER's TAXSIM program (http://users.nber.org/~taxsim/) to calculate after-tax returns.

rests on the assumption that the average rate of risk aversion, as captured by the time-invariant parameter $\gamma$, underestimates the '*true*' rate of risk aversion given major natural disasters. The underestimation of $\gamma$ has a direct impact on the CCAPM's pricing errors as it overvalues (undervalues) the stochastic discount factor when the growth in consumption is greater (smaller) than one. Accordingly, the overvalued (undervalued) stochastic discount factor translates into more positive (negative) pricing errors.

We proceed by estimating the following fixed-effects regression model:

$$\varepsilon_{j,t} = \gamma C + \delta 1_{cg} DIS + TIME + \xi_{j,t}$$

$$1_{cg} = \begin{cases} +1 \text{ when CG } > 1 \\ -1 \text{ when CG } < 1 \end{cases} \tag{8}$$

where $\varepsilon_{j,\,t}$ is the pricing error for the muni return in state *j* for month *t*. *C* is a matrix of control variables that also vary by state and month. The relation between disasters and risk aversion may suffer from an omitted-variable bias if variables other than risk aversion both affect the errors and are affected by disasters. We include two variables in the model that are plausibly linked to consumption, and hence to the variation in the CCAPM's pricing errors following disasters. The first variable is the monthly variations in state-level coincident indexes.[8] That indicator gives valuable information on the current local economic conditions (Pirinsky and Wang, 2006) and may capture plausible changes in local growth rates. The second variable is the monthly changes in Zillow's state-level housing price indexes that inform on typical home value.[9] Houses often are the most valuable asset of households and can be wrecked by disasters. Campbell and Cocco (2007) show that changes in house prices may signal shifts in consumption patterns. $\gamma$ is the vector of the coefficients of the control variables. *DIS* is a matrix that includes the sum of disaster-driven damages that occurred in a state over several mutually exclusive time periods. The literature offers few insights regarding the time period during which disasters may impact risk taking behavior. Indeed, in their review of the literature Noy and DuPont (2016) conclude that researchers have not reached consensus concerning the long-term consequences of natural disasters. Accordingly, we test for a disaster-related effect over a period of a few years. $1_{cg}$ is an indicator variable that takes the value of plus (minus) one when the gross consumption growth CG is greater (smaller) than one. The indicator variable ensures that the relation between $\varepsilon_{j,\,t}$ and $1_{cg}DIS$ is always positive (negative) if disasters are to increase (decrease) risk aversion. A disaster-related increase in risk aversion implies a positive and significant value for $\delta$ while a disaster-related decrease in risk aversion entails a negative and significant value. *TIME* are months fixed effects. The residuals $\xi_{j,t}$ are clustered by state.

## 5. Results

In this section, we present our main results associated with our two estimation approaches and discuss the implications of our results.

### 5.1. Estimation approach with a single rate of risk aversion

We begin by examining the model fit of the first CCAPM described by Eqs. (3)–(6). To this end, we fix the disaster-related risk aversion coefficient $\gamma^{DIS}$ to zero and observe the fit of the base model.

The average pricing error reaches 0.0281 percent. The errors amount to about 8 percent of the test asset returns when compared with the average return of 0.35 percent per month. It is difficult to judge whether relative pricing errors of 8 percent translate into good or poor model performance given that no previous studies used state-level muni indexes as test assets in a CCAPM. Nevertheless, the finding that no rate of risk aversion makes the average pricing error exactly zero is a common result in the literature. Several features or limitations of the model may help to explain the non-zero errors. Among them, we note the time-invariance of the parameters as well as the dependence of municipal bond returns not only on investor preferences but also on the effect of market frictions that are not accounted for in the CCAPM. Related to the CCAPM's errors, Jacobs et al. (2005) argue that one should be "*looking for [parameters] that yield a pricing error that is statistically indistinguishable from zero*" (p.13). Following Jacobs et al., we compute a standard deviation of the pricing errors of 0.0161 percent. Thus, the average pricing error is 1.75 standard deviations from zero so that the pricing errors in our model are not statistically significantly different from zero if we assume asymptotic normality.

As for the estimated values of the parameters, we obtain $\hat{\beta} = 0.9984$ and $\hat{\gamma}^{US} = 1.7752$. Both estimates are significantly different from zero at the 0.01 confidence level. As expected, the value of the impatience parameter is slightly less than one. Many well-known studies argue that economically reasonable values for the coefficient $\gamma^{US}$ should range between one and two (Arrow, 1971; Friend and Blume, 1975), and Mehra and Prescott (1985) restrict the value of $\gamma$ to be a maximum of ten. In this context, our empirically obtained estimate of $\gamma^{US}$ appears plausible.

[8] Details on the construction of the coincident indexes and data are available on the website of the Federal Reserve Bank of Philadelphia (https://www.philadelphiafed.org/research-and-data/regional-economy/indexes/coincident/).

[9] Details on the construction of the house price indexes and data are available on the Zillow's website (https://www.zillow.com/research/data/).

**Table 2**
Results of the first estimation approach.
Table 2 provides the estimated parameter values resulting from the first estimation approach. The CCAPM is structured as:

$$0 = \mathrm{E}\left[\beta \frac{C_{j,t}}{C_{j,t-1}}^{-(\gamma^{US}+\gamma^{DIS}DIS_{j,t-k})}(R_{j,t} - R_{f,t})\right]$$

Where $\frac{C_{j,t}}{C_{j,t-1}}$ is the monthly consumption growth in state j inferred from electricity usage, $R_{j,\,t}$ is the monthly return of a municipal bond index grouping issuers located in state j and $DIS_{j,t-k}$ is the total amount of disaster-related damage expressed as a fraction of state-level GDP in state $j$ in the $k^{th}$ previous month. Three parameters are estimated in the model: $\beta$ reflects investor impatience, $\gamma^{US}$ is a state- and time- invariant relative risk aversion coefficient and $\gamma^{DIS}$ is the main parameter of interest that reflects the variation in mean risk aversion associated with disaster-related damage. Parameter values are estimated with GMM. Standard errors are reported in the parentheses.

| Parameter | $k ==-1$ | $k = 0$ | $k = 1$ | $k = 2$ | $k = 3$ | $k = 4$ | $k = 5$ | $k = 6$ |
|---|---|---|---|---|---|---|---|---|
| $\beta$ | 0.9917*** | 0.9987*** | 0.9985*** | 0.9985*** | 0.9978*** | 0.9911*** | 0.9991*** | 0.9985*** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| $\gamma^{US}$ | 1.7548*** | 1.7634*** | 1.6537*** | 1.6535*** | 1.7843*** | 1.8546*** | 1.7037*** | 1.8157*** |
| | (0.0079) | (0.0078) | (0.0079) | (0.0078) | (0.0081) | (0.0080) | (0.0076) | (0.0078) |
| $\gamma^{DIS}$ | −0.1359 | 0.1513 | 2.8127*** | 1.7600*** | 0.6818*** | 0.3026 | 0.2509 | −0.3183 |
| | (0.2661) | (0.1764) | (0.2143) | (0.1678) | (0.1905) | (0.2085) | (0.4840) | (0.4440) |

*** indicate statistical significance at the 0.01 level.

We then include the disaster-related risk aversion coefficient $\gamma^{DIS}$ in our estimation and generate our main results. Table 2 displays the resulting coefficients when disaster losses sustained in the previous $k^{th}$ month are considered. We observe that the levels of disaster damage incurred in the last three months ($k = 1, 2, 3$) are associated with a positive and highly significantly value for $\gamma^{DIS}$. The value of $\gamma^{DIS}$ remains positive but is no longer statistically significant when we consider losses beyond three months ago. This result is consistent with a short-term disaster-related increase in risk aversion. The effect of disasters on risk aversion appears economically important. The estimated parameter values imply that a major disaster with losses amounting to 0.5 percent of a state's GDP would increase risk aversion from the average of 1.65 to about 3.06 in the month following the event. This represents a temporary hike of more than 80 percent. Also, the fact that the estimated values of $\gamma^{DIS}$ gradually decrease from $k = 1$ to $k = 6$ may be interpreted as a sign that the level of risk aversion reverts to its long-term average over a few months.

We perform a first test of robustness by examining the effect of *future* disaster losses on risk aversion. To this end, we use negative values ranging between −1 and −6 for $k$. Finding a statistically significant value for the parameter $\gamma^{DIS}$ would be evidence against our model. We only report in Table 2 the result for $k = -1$ given that each iteration leads to the same conclusion. As expected, future disaster losses have no significant effect on $\gamma^{DIS}$. Note that we keep the number of parameters constant in all of our tests in part for comparison purposes, and in other parts, to keep the optimization problem relatively parsimonious in order to avoid convergence issues. We provide more evidence on the time-variation of risk aversion using our second estimation approach in the next section.

### *5.2. Estimation approach with one rate of risk aversion per state*

We now proceed with our second approach based on the conventional canonical CCAPM of Hansen and Singleton (1983) estimated at the state-level. In terms of model fit, we obtain risk aversion coefficients resulting in average pricing errors of zero in 39 states out of 50. The three states with the highest average pricing errors in proportion to muni returns are Hawaii (0.88 percent), Maine (0.85 percent) and Alaska (0.82 percent). The higher pricing errors come from the fact that these three states have the lowest mean consumption growth and, by far, the highest relative standard deviations of consumption growth. Pricing errors are statistically indistinguishable from zero in all states, including AK, HI and ME.

State-level risk aversion is positive in all states except Hawaii ($\hat{\gamma}_{HI} = -5.12$). Apart from Hawaii, risk aversion varies between 1.57 (Oklahoma) and 14.99 (Nebraska) with a median of 3.50. We examine the plausibleness of the geographical distribution by comparing the state variations in $\widehat{\gamma_j}$ with the volume of direct written life and health insurance premiums per capita from the annual statement of the National Association of Insurance Commissioners (NAIC) for the year 2010 (Schedule T), which is one documented indicator of risk aversion (Szpiro, 1986). We obtain a positive and significant cross-state Spearman's correlation coefficient ($\rho^{sp}$) of 0.27 between risk aversion and the demand for insurance series.

Next, we estimate Eq. (8) and look at the relationship between pricing errors and disasters. To this end, we include in the panel regression framework the total disaster losses by quarter over 14 quarters. The two first quarters account for upcoming disaster losses and should be uncorrelated to the pricing errors. The following 12 quarters allows us to follow the effect of disasters on pricing errors over three years. Here we favor aggregating losses over quarters rather than using monthly losses in order to account for the facts that some events are relatively long-lived and entail damage or adverse psychological consequences that may emerge over several months (Norris et al., 2002; Phifer and Norris, 1989). Based on the results of the preceding section, we expect to observe statistically significant positive errors at least in the first quarter following disaster losses. Table 3 presents the estimation results. For ease of illustration, Fig. 4 displays an 'event-study' picture which shows the dynamics of pricing errors over time as a function of disaster losses.

**Table 3**
Effect of disaster losses on CCAPM's pricing errors.
Table 3 displays the results of the event study based on the pricing errors arising from the GMM estimation of the CCAPM model at the state-level. The regression model is:

$$\varepsilon_{j,t} = \delta 1_{cg} DIS_{j,t} + \gamma C_{j,t} + TIME + \xi_{j,t}$$
$$1_{cg} = \begin{cases} +1 \text{ when CG} > 1 \\ -1 \text{ when CG} < 1 \end{cases}$$

Where $\varepsilon_{j,\,t}$ is the pricing error for the municipal bond index return in state j for month t. DIS is a matrix of disaster-driven damage expressed as a fraction of the state GDP over several time periods. $1_{cg}$ is an indicator variable that takes the value of plus (minus) one when the gross consumption growth CG is greater (smaller) than one. The indicator variable ensures that the relation between $\varepsilon_{j,\,t}$ and $1_{cg}DIS$ shall always be positive (negative) if disasters are to increase (decrease) risk aversion. $\delta$ is the vector containing the estimates of the main coefficient of interest that convey the effect of disasters-related losses on risk aversion. $C$ is a matrix of control variables that includes the growth of the state coincident indexes (CI) and of the state housing price indexes (HPI) and TIME are months fixed effects. Standard errors are clustered by state.

| | | Estimate | Standard Error |
|---|---|---|---|
| Controls | CI | −0.00167 | 0.00188 |
| | HPI | 0.00024 | 0.00058 |
| Upcoming disaster | $1_{cg}$*$DIS_{-6,-4}$ | 0.00022 | 0.00152 |
| losses | $1_{cg}$*$DIS_{-3,-1}$ | 0.00035 | 0.00040 |
| Past disaster losses | $1_{cg}$*$DIS_{1,3}$ | 0.00184*** | 0.00036 |
| | $1_{cg}$*$DIS_{4,6}$ | 0.00173 | 0.00151 |
| | $1_{cg}$*$DIS_{7,9}$ | 0.00009 | 0.00032 |
| | $1_{cg}$*$DIS_{10,12}$ | −0.00029 | 0.00056 |
| | $1_{cg}$*$DIS_{13,15}$ | 0.00090** | 0.00039 |
| | $1_{cg}$*$DIS_{16,18}$ | −0.00025 | 0.00034 |
| | $1_{cg}$*$DIS_{19,21}$ | −0.00043 | 0.00032 |
| | $1_{cg}$*$DIS_{22,24}$ | 0.00027 | 0.00040 |
| | $1_{cg}$*$DIS_{25,27}$ | 0.00016 | 0.00047 |
| | $1_{cg}$*$DIS_{28,30}$ | −0.00021 | 0.00053 |
| | $1_{cg}$*$DIS_{31,33}$ | 0.00007 | 0.00037 |
| | $1_{cg}$*$DIS_{34,36}$ | 0.00006 | 0.00035 |
| Fixed effects: Months | | YES | |
| | R-square | 0.4071 | |
| | Observations | 7750 | |

**, *** indicate statistical significance at the 0.05 and 0.01 level, respectively.

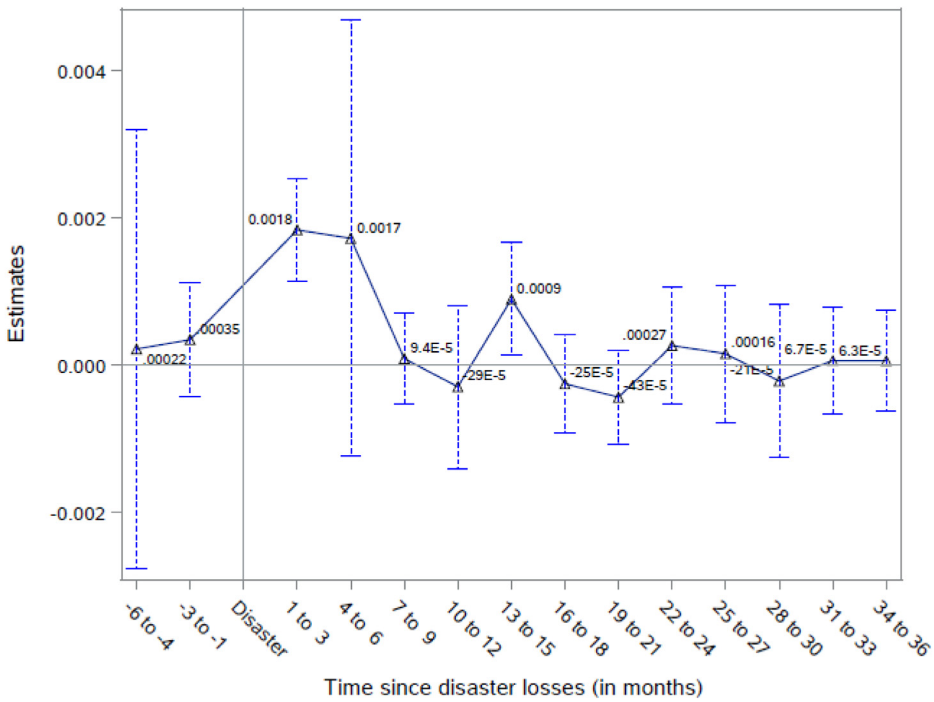


**Fig. 4.** Effect of disasters on CCAPM's pricing errors over time.

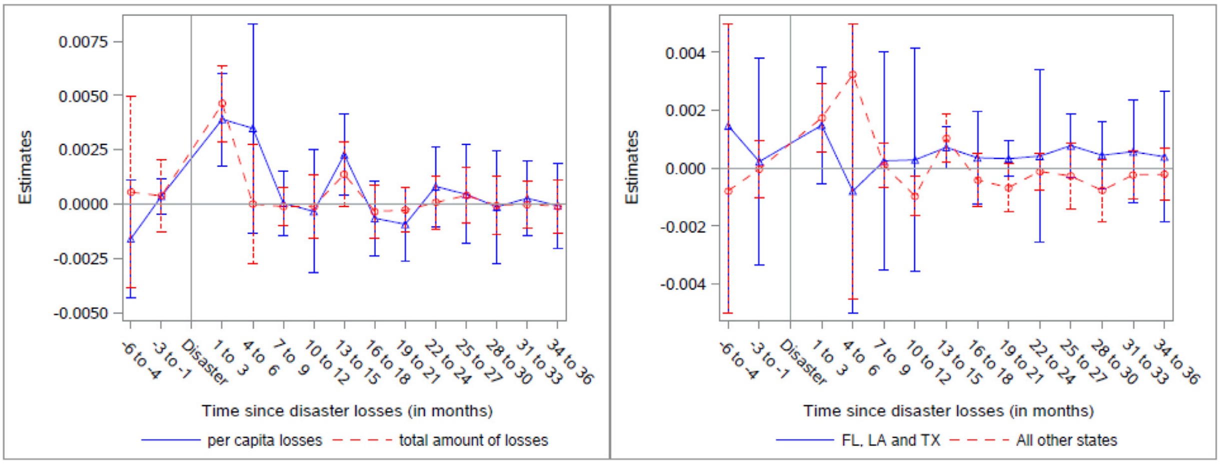


**Fig. 5.** Effect of disasters on CCAMP's pricing errors using alternative measure of disaster losses and exploiting differences in ex-ante disaster risk.

We observe positive and statistically significant pricing errors over the first quarter following disasters. This result is coherent with the one obtained from our first estimation approach and suggests a short-term disaster-related increase in risk aversion. As expected, future disaster losses have no significant impact on pricing errors. Interestingly, we observe a highly positive but very volatile (insignificant) coefficient in the second quarter following disasters. Surprisingly, we observe another significant spike in pricing errors in the 5th quarter following an event. The emotion channel can be exploited to provide tentative explanations for the surge in pricing errors one year after disasters. Among other things, news networks and the print media often air throwback reports of major events that occurred one year ago so that disaster induced emotions might resurface.[10] In this respect, Adessky and Freedman (2005) note that fear structures associated with attributes of the adverse event are retrieved and reinforced when information related to the event are presented. In addition, stress and other negative emotions likely to increase risk aversion may be exacerbated with the arrival of the 'disaster season' in states with cyclical disaster risk (Bolin, 1982). Such an explanation is consistent with the findings of Phifer and Norris (1989) who observe that some stimuli such as the anniversary of disasters help explain seasonal fluctuations in the level of psychological symptoms. A competing possibility would be that our results capture the effect of cyclical disasters. We test for this possibility by investigating whether or not 12-month old disaster losses have some explanatory power over current disasters at the state level. We find evidence of a statistically significant relation in only four states: Tennessee, North Dakota, Minnesota and Oregon. In an unreported test, we repeat our panel estimation excluding these four state and the results are materially unchanged.

### 5.3. Alternative measures of disaster losses

We further examine the robustness of our results by testing alternative ways to express disaster losses. Our main analysis employs losses as a fraction of states' GDP. We now re-estimate our panel regression using the total amount of losses per month by state, as well as the amount of per capita losses. We present the results of the alternative measures of disaster losses in Panel A of Fig. 5. Note that we multiply the residuals by one thousand (one billion) when using per capita (total) losses to obtain estimated parameter values associated with the disaster-related variables of the same order of magnitude as in Table 3. We observe that using per capita losses yields the exact same pattern as using losses as a fraction of GDP. Employing the total amount of disaster losses also reveals that the CCAPM's pricing errors are significantly positive in the first and fifth quarters following disasters, although losses from the preceding fifth quarter are only significant at the 0.10 level.

### 5.4. Ex-ante perceived risk

We continue with our robustness tests by examining the effect of the perceived level of disaster risk. As we cannot observe investors' beliefs about disaster risk, we assume that the perceived riskiness correlates with historical disasters losses. We rationalize this assumption using the availability heuristic of Tversky and Kahneman (1974) that foretells that individuals judge the probability of an event based on instances that come readily to mind. We calculate the average amount of losses on GDP by state and seasons-of-the-year (quarters) on the 1996 to 2004 period and use this historical average to distinguish expected losses (losses below or equal to the historical quarterly average) from unexpected losses (losses

[10] A Google search on October 15, 2019, for example, for "anniversary of hurricane katrina" results in 204,000 hits.

**Table 4**
Effect of expected versus unexpected disaster losses.
Table 4 presents the effect of disaster losses on the CCAPM's pricing errors when losses are split into two components: expected and unexpected losses. The estimation process and the dependant variable are described in Table III. Expected losses are the losses below or equal to the state-level historical quarterly average. Unexpected losses are the losses exceeding the state-level historical quarterly average. Historical averages are the simple mean of disaster losses expressed as a fraction of states' GDP between 1996 and 2004 by state and quarter-of-the-year. Standard errors are clustered by state.

| | | Expected disaster losses | | Unexpected disaster losses | |
|---|---|---|---|---|---|
| | | Estimate | Standard Error | Estimate | Standard Error |
| Controls | CI | −0.00138 | 0.00191 | −0.00168 | 0.00188 |
| | HPI | 0.00035 | 0.00056 | 0.00024 | 0.00058 |
| Upcoming disaster losses | $1_{cg}{}^{*}DIS_{-6,-4}$ | 0.26207 | 0.16254 | 0.00021 | 0.00182 |
| | $1_{cg}{}^{*}DIS_{-3,-1}$ | 0.01754 | 0.06065 | 0.00035 | 0.00041 |
| Past disaster losses | $1_{cg}{}^{*}DIS_{1,3}$ | 0.04225 | 0.05917 | 0.00183*** | 0.00037 |
| | $1_{cg}{}^{*}DIS_{4,6}$ | 0.14542 | 0.20067 | 0.00172 | 0.00177 |
| | $1_{cg}{}^{*}DIS_{7,9}$ | 0.04267 | 0.06206 | 0.00005 | 0.00031 |
| | $1_{cg}{}^{*}DIS_{10,12}$ | −0.03655 | 0.03031 | −0.00029 | 0.00057 |
| | $1_{cg}{}^{*}DIS_{13,15}$ | 0.05477 | 0.05666 | 0.00085** | 0.00039 |
| | $1_{cg}{}^{*}DIS_{16,18}$ | 0.04067 | 0.07089 | −0.00029 | 0.00034 |
| | $1_{cg}{}^{*}DIS_{19,21}$ | 0.00295 | 0.05636 | −0.00044 | 0.00032 |
| | $1_{cg}{}^{*}DIS_{22,24}$ | 0.01527 | 0.06417 | 0.00029 | 0.00040 |
| | $1_{cg}{}^{*}DIS_{25,27}$ | −0.02734 | 0.04130 | 0.00017 | 0.00046 |
| | $1_{cg}{}^{*}DIS_{28,30}$ | 0.08705 | 0.12685 | −0.00017 | 0.00051 |
| | $1_{cg}{}^{*}DIS_{31,33}$ | −0.03757 | 0.03931 | 0.00008 | 0.00035 |
| | $1_{cg}{}^{*}DIS_{34,36}$ | 0.02601 | 0.06219 | −0.00004 | 0.00037 |
| Fixed effects: Months | | YES | | YES | |
| | R-square | 0.4091 | | 0.4070 | |
| | Observations | 7700 | | 6500 | |

**, *** indicate statistical significance at the 0.05 and 0.01 level, respectively.

exceeding the historical quarterly average). We then estimate Eq. (8) separately for expected and unexpected disaster losses. We report the results in Table 4.

We observe that disaster losses with similar amplitude to those experienced in the past have no significant explanatory power on the CCAPM's pricing errors. Indeed, while we observe positive coefficients for the 1–3 and 13–15 month periods, these coefficients are not statistically significant at the 0.05 level. However, losses exceeding the level investors are accustomed to have a clear positive impact on pricing errors in the first and fifth quarter following disasters and are consistent with our previous results. Thus, this suggests that the effect of disasters on risk aversion seems to come mostly from relatively large disasters that cause damage beyond the levels experienced in the past. We reach a similar conclusion if we use the historical highest loss by state and quarter instead of the historical mean.

Next, we ask ourselves if our results are attributable to a handful of extreme disasters or to a handful of states. Among other things, it might be the case if emotions are spread by news coverage and if some disasters – or disaster prone states – receive particularly intense media attention. Hurricanes are one category of disasters that cause the highest level of damages, receive the most media attention, and hit some states much more often than other states. We observe that three states experienced more than $50 billion in disaster losses over the 1996–2017 period: Texas ($143 bil.), Louisiana ($84 bil.) and Florida ($60 bil.), and that most losses in these states are associated with hurricanes. In Panel B of Fig. 5, we observe how CCAPM's pricing errors in these three states vary following disasters relative to elsewhere. For ease of illustration, we truncate the somewhat large confidence intervals associated with the second period following disasters (months 4 to 6). We see that pricing errors for the three hurricane prone states reach statistical significance in no period, but have estimates mostly in line with those of the other states. We caution readers not to over interpret the absence of statistical significance. The smaller number of observations used to estimate the coefficients of the disaster variables in hurricane prone states plausibly explains the larger confidence intervals. In short, the results are consistent with a disaster-related increase in risk aversion and the increase is not limited to (or caused by) the largest disasters or damaged states.

### *5.5. Alternative explanatory channel: background risk*

Previous sections present and discuss our main results from the perspective of a disaster-induced variation in risk aversion caused by emotions. We now examine the merits of an alternative explanatory channel where the temporary increase in risk aversion is triggered by changes in background risk. Disasters arguably bring on a period of uncertainty before the scale and full impact of the event becomes known. That higher uncertainty is felt by investors and can be seen as an increase in background risk, which is the risk that people cannot avoid, diversify away or insure against. Increases in background risk are known to make people take fewer risks (Cameron and Shah, 2015; Gollier and Pratt, 1996). We formally examine this explanatory channel by developing a metric of background risk.

To this end, we follow the reasoning of Bacon et al. (2020) who use the volatility of a stock market index as a measure of background risk and infer background risk from the volatility of our municipal bond indexes. The repeated sales

**Table 5**
The background risk channel.
Table 5 examines the effect of disaster losses on background risk using the one-month variation in parameter's adjusted standard errors of the repeated-sale regression used to estimate municipal bond indexes returns ($\boldsymbol{BR_t} = \boldsymbol{\sigma}_{\hat{\beta}_{j,t}} / \boldsymbol{\sigma}_{\hat{\beta}_{j,t-1}}$) as measure of background risk. Description of the repeated sale approach can be found in online supplementary appendix II. The first model examines the effect of disaster losses on background risk. The second model employs the CCAPM's pricing errors as the dependant variable and adds current and lagged values of background risk as additional independent variables. As in Table 3, $1_{cg}$ is an indicator variable that takes the value of plus (minus) one when the gross consumption growth CG is greater (smaller) than one. The indicator variable ensures that the relation between $\varepsilon_{j,\,t}$ and $1_{cg}BR$ shall always be positive (negative) if background risk is to increase (decrease) risk aversion. Standard errors are clustered by state.

| | Model 1Y = Background risk ($BR_t$) | | | Model 2Y = CCAPM's pricing errors | | |
|---|---|---|---|---|---|---|
| | | Estimate | Standard Error | | Estimate | Standard Error |
| Controls | CI | −0.00561 | 0.02030 | CI | −0,00,211 | 0,00,205 |
| | HPI | −0.02303* | 0.01323 | HPI | 0,00,117 | 0,00,082 |
| Upcoming disaster | $DIS_{-6,-4}$ | −0.00009 | 0.00095 | $1_{cg}$*$DIS_{-6,-4}$ | 0,00,026 | 0,00,154 |
| losses | $DIS_{-3,-1}$ | 0.00013 | 0.00068 | $1_{cg}$*$DIS_{-3,-1}$ | 0,00,039 | 0,00,039 |
| Past disaster losses | $DIS_{1,3}$ | 0.00305 | 0.01429 | $1_{cg}$*$DIS_{1,3}$ | 0,00,190*** | 0,00,032 |
| | $DIS_{4,6}$ | 0.01970*** | 0.00688 | $1_{cg}$*$DIS_{4,6}$ | 0,00,213 | 0,00,151 |
| | $DIS_{7,9}$ | 0.00189 | 0.01421 | $1_{cg}$*$DIS_{7,9}$ | 0,00,002 | 0,00,032 |
| | $DIS_{10,12}$ | −0.00702 | 0.00690 | $1_{cg}$*$DIS_{10,12}$ | −0,00,029 | 0,00,057 |
| | $DIS_{13,15}$ | 0.00244 | 0.00345 | $1_{cg}$*$DIS_{13,15}$ | 0,00,086** | 0,00,039 |
| | $DIS_{16,18}$ | −0.00264 | 0.00437 | $1_{cg}$*$DIS_{16,18}$ | −0,00,026 | 0,00,033 |
| | $DIS_{19,21}$ | 0.00840 | 0.00775 | $1_{cg}$*$DIS_{19,21}$ | −0,00,042 | 0,00,031 |
| | $DIS_{22,24}$ | −0.00707 | 0.00737 | $1_{cg}$*$DIS_{22,24}$ | 0,00,027 | 0,00,042 |
| | $DIS_{25,27}$ | 0.00194 | 0.00354 | $1_{cg}$*$DIS_{25,27}$ | 0,00,017 | 0,00,047 |
| | $DIS_{28,30}$ | −0.00089 | 0.00577 | $1_{cg}$*$DIS_{28,30}$ | −0,00,017 | 0,00,052 |
| | $DIS_{31,33}$ | 0.00630* | 0.00360 | $1_{cg}$*$DIS_{31,33}$ | 0,00,008 | 0,00,035 |
| | $DIS_{34,36}$ | −0.00518 | 0.00874 | $1_{cg}$*$DIS_{34,36}$ | 0,00,009 | 0,00,036 |
| Background risk | | | | $1_{cg}$*$BR_t$ | −0,00,020 | 0,00,224 |
| | | | | $1_{cg}$*$BR_{t-1}$ | 0,00,057*** | 0,00,011 |
| Fixed effects: Months | | YES | | | YES | |
| R-square | | 0.4301 | | | 0.4051 | |
| Observations | | 7650 | | | 7600 | |

*, **, *** indicate statistical significance at the 0.10, 0.05 and 0.01 level, respectively.

approach used to obtain our municipal bond indexes relies on an autoregressive process to estimate coefficients associated with monthly dummies. As dummy variables are used as independent variables, their estimated coefficients and associated standard errors are comparable over time and states. Standard errors measure the uncertainty about the true value of the muni indexes each month for each state. However, standard errors are inversely proportional to the number of observations used to estimate the coefficients and more trades occur toward the end than near the beginning of our sample. Therefore, we retain the part of the standard errors that is unrelated to the number of monthly state-level observations in the repeat sales regression. We interpret the one-month state-level variation in the adjusted standard errors as a measure of background risk.

Using a fixed-effects regression model similar to that of Eq. (8), we run two separate regressions. In the first model, we examine the relation between past disaster losses and background risk. In the second model, we include our measure of background risk (both current and one-lag) as additional explanatory variables into our main regression model. The aim of adding these variables is to determine whether the effect of disaster losses captures changes in background risk. The second regression model is specified as:

$$\varepsilon_{j,t} = \gamma C + \delta 1_{cg} DIS + \lambda_{BR_t} 1_{cg} BR_t + \lambda_{BR_{t-1}} 1_{cg} BR_{t-1} + TIME + \xi_{j,t}$$

$$1_{cg} = \begin{cases} +1 \text{ when CG } > 1 \\ -1 \text{ when CG } < 1 \end{cases} \tag{9}$$

Note that we associate the $1_{cg}$ indicator to the background risk variable. Everything else being equal, we expect that the relation between $\varepsilon_{j,\,t}$ and $1_{cg}BR$ shall always be positive (negative) if the one-month change in background risk is to increase (decrease) risk aversion. The other variables are defined as in Eq. (8). As done previously, standard errors are clustered by state. We report the result of these analyses in Table 5.

The results of the first model suggest that some disaster-related losses from past quarters have some explanatory power over changes in background risk. Surprisingly, although the coefficient of $DIS_{1,\,3}$ is positive as expected, it is not statistically significant at any conventional level. We rather observe a positive and highly significant coefficient associated to $DIS_{4,\,6}$. Disaster losses from farther in the past have no explanatory power over the variations in background risk. This result suggests that disasters do affect background risk, but it seems to take a few months before the aftermaths of the events translate into a widespread heighten perception of uncertainty. Interestingly, we note that the largest increase in background risk is linked to the global financial crisis and is associated with the October 2008 month dummy.

In the second model, we note that the addition of the background risk variable has no material impact on the estimated coefficients of the disaster losses variables. Thus, the relationship between pricing errors and disasters remains consistent with an emotion-induced increase in risk aversion. Opposing our base expectation, the contemporary variation in background risk has no explanatory power over the pricing errors. However, we observe that the coefficient of the lagged value of our background risk variable is positive and highly significant, which upholds the consensus in the literature that higher background risk makes individuals more risk averse.

### *5.6. Additional robustness tests*

Last, we run a series of additional robustness tests and report the results in the online appendix. Among other things:

(i) We make sure that our event-study results are robust to the use of alternative econometric models. We acknowledge that the pricing errors $\varepsilon_{j,\,t}$ are measured with errors. Consequently, we re-estimate Eq. (8) using the M-estimation method developed by Huber (1973). This method produces estimates that remain reliable in the presence of various types of noise and is robust to outliers in the dependant variable. Also, the fact that the M-estimation put less weight on outliers than a least-squares regression makes it more difficult to find a significant relationship between disasters and risk aversion as large disaster-induced pricing errors are discounted in the analysis. We also test for alternative versions of Eq. (8) that include state-level fixed-effects, spatial correlation among residuals and robust (sandwich) standard errors. Our main conclusions remain the same under the alternative models.

(ii) We implement a test based on placebo treatment where we shift pricing errors by one year in the future. Our main conclusions remain.

(iii) We combine disaster losses of the last quarter into four quartile-based categories in order to mitigate the effect of any systematic measurement error in the disaster losses. We create dummy variables from the loss categories and estimate the event-study regression. Results suggest that the effect of disasters on pricing errors positively correlates with the intensity of disasters, which is consistent with basic economic intuition and with our main results.

(iv) We expand our analysis of the time variation in risk aversion by using the historical total annual disaster losses by state up to nine years in the past. Only the recent yearly loss variable has a significant positive impact on pricing errors.

(v) We examine how various demographic and economic characteristics of the representative investors, as well as disaster-related losses, succeed in explaining the variation of risk aversion over time and states. The analysis of the determinant of time-varying risk aversion informs that past disaster losses have some explanatory power regarding time variations in risk aversion. Yet, as the loss variable is only significant at the 0.1 level, disasters appear to be more of a second-order than a first-order determinant.

(vi) We investigate the merits of an alternative explanatory channel under which the observed increase in risk-aversion could be caused by municipal bond supply differentials. The result does not support supply differential as a valid alternative channel to explain the observed temporary disaster-induced increase in risk aversion.

## 6. Conclusion

In this paper, we study asset pricing in the wake of disasters at the regional level and examine the assumption that extreme weather events cause temporary variations in risk aversion. We retain the well-known CCAPM framework and estimate risk aversion using state-level consumption data and state-level series of asset returns. In a first analytical approach, we separate the risk aversion parameter into two components, one of them varying by state and time as a function of the amount of disaster losses. We find evidence consistent with higher risk aversion in the months following losses. In a second analytical approach, we examine the CCAPM's pricing errors and observe a systematic pattern between the pricing errors and disaster-related losses that supports a disaster-driven increase in risk aversion story. The increase is economically and statistically significant but temporary. Risk aversion seems to increase in the first quarter following extreme weather events and resurfaces one year later (anniversaries) in the fifth quarter following losses. These conclusions are robust for various measures of disaster losses and not restricted to a few high-risk states.

The assessment of risk preferences implied by asset prices at the regional level is, by itself, an original contribution to the economic literature. Yet, the importance of this study rests to a large extent on the evidence that extreme weather events have a material impact on financial risk-taking behavior at the aggregate level. This is particularly true given the consensus in the scientific community that climate change should increase the frequency and intensity of disasters. A lower propensity to take financial risks has many major implications regarding (i) economic growth as it may impede business start-ups and impede companies from making risky investments; (ii) financial markets and portfolio management as it may adversely affect asset prices by raising required returns; and (iii) public management decision making as it potentially augments the perceived value of risk management programs and infrastructures.

## Declarations of Competing Interest

The authors report no potential conflicts of interest.

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## References

Adessky, R.S., Freedman, S.A., 2005. Treating survivors of terrorism while adversity continues. J. Aggress. Maltreat. Trauma 10, 443–454. https://doi.org/10.1300/J146v10n01_03.
Ang, A., Bhansali, V., Xing, Y., 2010. Taxes on tax-exempt bonds. J. Finance. 65, 565–601. https://doi.org/10.1111/j.1540-6261.2009.01545.x.
Arrow, K.J., 1971. The theory of risk aversion. In: Helsinki, Y.J.S. (Ed.), Aspects of the Theory of Risk Bearing. Markham Publ. Co., Chicago, pp. 90–120.
Bacon, P.M., Conte, A., Moffatt, P.G., 2020. A test of risk vulnerability in the wider population. Theory Decis. 88, 37–50. https://doi.org/10.1007/s11238-019-09708-5.
Bird, E.J., Hagstrom, P.A., 1999. The wealth effects of income insurance. Review Income Wealth 45, 339–352. https://doi.org/10.1111/j.1475-4991.1999.tb00344.x.
Bolin, R.C., 1982. Long-term Family Recovery from Disaster. University of Colorado Institute of Behavioral Science, Boulder, CO.
Brav, A., Constantinides, G.M., Geczy, C.C., 2002. Asset pricing with heterogeneous consumers and limited participation: empirical evidence. J. Polit. Econ. 110, 793–824.
Breeden, D.T., Litzenberger, R.H., 1978. Prices of state-contingent claims implicit in option prices. J. Bus. 51, 621–651.
Brown, P., Daigneault, A.J., Tjernström, E., Zou, W., 2018. Natural disasters, social protection, and risk perceptions. World Dev. 104, 310–325. https://doi.org/10.1016/j.worlddev.2017.12.002.
Cameron, L., Shah, M., 2015. Risk-taking behavior in the wake of natural disasters. J. Hum. Resour. 50, 484–515. https://doi.org/10.3368/jhr.50.2.484.
Campbell, J.Y., Cocco, J.F., 2007. How do house prices affect consumption? Evidence from micro data. J. Monet. Econ. 54, 591–621. https://doi.org/10.1016/j.jmoneco.2005.10.016.
Campbell, J.Y., Cochrane, J.H., 2000. Explaining the poor performance of consumption-based asset pricing models. J. Financ. 55, 2863–2878.
Campbell, J.Y., Cochrane, J.H., 1999. By force of habit: a consumption-based explanation of aggregate stock market behavior. J. Polit. Econ. 107, 205–251. https://doi.org/10.1086/250059.
Campbell, T.S., 1980. On the extent of segmentation in the municipal securities market. J. Money Credit Bank. 12, 71–83. https://doi.org/10.2307/1991594.
CEMHS, 2018. Spatial hazard events and losses database for the United States (SHELDUS) Version 17.0 (Online Database). Center for Emergency Management and Homeland Security, Arizona State University, Phoenix, AZ.
Chan, Y.L., Kogan, L., 2002. Catching up with the Joneses: heterogeneous preferences and the dynamics of asset prices. J. Polit. Econ. 110, 1255–1285. https://doi.org/10.1086/342806.
Chen, H., Joslin, S., Tran, N.-K., 2012. Rare disasters and risk sharing with heterogeneous beliefs. Rev. Financ. Stud. 25, 2189–2224. https://doi.org/10.1093/rfs/hhs064.
Chuang, Y., Schechter, L., 2015. Stability of experimental and survey measures of risk, time, and social preferences: a review and some new results. J. Dev. Econ. 117, 151–170. https://doi.org/10.1016/j.jdeveco.2015.07.008.
Cochrane, J.H., 2005. Asset Pricing, Revised Ed. Princeton University Press, Princeton, New Jersey.
Constantinides, G., Duffie, D., 1996. Asset pricing with heterogeneous consumers. J. Polit. Econ. 104, 219–240.
Da, Z., Huang, D., Yun, H., 2017. Industrial electricity usage and stock returns. J. Financ. Quant. Anal. 52, 37–69. https://doi.org/10.1017/S002210901600079X.
Da, Z., Yang, W., Yun, H., 2015. Household production and asset prices. Manage Sci. 62, 387–409. https://doi.org/10.1287/mnsc.2014.2130.
Da, Z., Yun, H., 2010. Electricity consumption and asset prices (SSRN Scholarly Paper No. ID 1608382). Social Science Research Network, Rochester, NY.
Do, L.P.C., Lin, K.-H., Molnár, P., 2016. Electricity consumption modelling: a case of Germany. Econ. Model. 55, 92–101. https://doi.org/10.1016/j.econmod.2016.02.010.
Donaldson, R.G., Kamstra, M., 1996. A new dividend forecasting procedure that rejects bubbles in asset prices: the case of 1929's stock crash. Rev. Financ. Stud. 9, 333–383. https://doi.org/10.1093/rfs/9.2.333.
Eckel, C.C., El-Gamal, M.A., Wilson, R.K., 2009. Risk loving after the storm: a Bayesian-network study of Hurricane Katrina evacuees. J. Econ. Behav. Org. Individual Dec.-Making, Bayesian Estimat. Market Des. 69, 110–124. https://doi.org/10.1016/j.jebo.2007.08.012.
Eeckhoudt, L., Gollier, C., Schlesinger, H., 2011. Economic and Financial Decisions Under Risk. Princeton University Press.
Epstein, L.G., Zin, S.E., 1991. Substitution, risk aversion, and the temporal behavior of consumption and asset returns: an empirical analysis. J. Polit. Econ. 99, 263–286. https://doi.org/10.1086/261750.
Feroz, E.H., Wilson, E.R., 1992. Market segmentation and the association between municipal financial disclosure and net interest costs. Account. Rev. 67, 480–495.
Fischer, P.J., 1983. Note, advance refunding and municipal bond market efficiency. J. Econ. Bus. 35, 11–20. https://doi.org/10.1016/0148-6195(83)90026-7.
Friend, I., Blume, M.E., 1975. The demand for risky assets. Am. Econ. Rev. 65, 900–922.
Gall, M., Borden, K.A., Cutter, S.L., 2009. When do losses count?: six fallacies of natural hazards loss data. Bull. Am. Meteorol. Soc. 90, 799–809. https://doi.org/10.1175/2008BAMS2721.1.
Goebel, J., Krekel, C., Tiefenbach, T., Ziebarth, N.R., 2015. How natural disasters can affect environmental concerns, risk aversion, and even politics: evidence from Fukushima and three European countries. J. Popul. Econ. 28, 1137–1180. https://doi.org/10.1007/s00148-015-0558-8.
Gollier, C., Pratt, J.W., 1996. Risk vulnerability and the tempering effect of background risk. Econometrica 64, 1109–1123. https://doi.org/10.2307/2171958.
Green, R.C., Hollifield, B., Schürhoff, N., 2007. Financial intermediation and the costs of trading in an opaque market. Rev. Financial Studies 20, 275–314. https://doi.org/10.1093/rfs/hhl012.
Greer, R.A., Denison, D.V., 2014. Does intrastate competition in segmented municipal bond markets affect interest costs? An empirical test of the preferred habitat hypothesis. Municipal Financ. J. 35, 1–15.
Guiso, L., Sapienza, P., Zingales, L., 2018. Time varying risk aversion. J financ econ. https://doi.org/10.1016/j.jfineco.2018.02.007.
Hanaoka, C., Shigeoka, H., Watanabe, Y., 2015. Do Risk Preferences Change? Evidence from Panel Data before and after the Great East Japan Earthquake (Working Paper No. 21400) National Bureau of Economic Research https://doi.org/10.3386/w21400 .
Hansen, L.P., Jagannathan, R., 1997. Assessing specification errors in stochastic discount factor models. J. Financ. 52, 557–590. https://doi.org/10.1111/j.1540-6261.1997.tb04813.x.
Hansen, L.P., Singleton, K.J., 1983. Stochastic consumption, risk aversion, and the temporal behavior of asset returns. J. Polit. Econ. 91, 249–265. https://doi.org/10.1086/261141.
Hendershott, P.H., Kidwell, D.S., 1978. The impact of relative security supplies: a test with data from a regional tax-exempt bond market. J. Money Credit Bank. 10, 337–347. https://doi.org/10.2307/1991512.
Huber, P.J., 1973. Robust regression: asymptotics, conjectures and monte carlo. Ann. Statis. 1, 799–821.

Jacobs, K., Pallage, S., Robe, M.A., 2005. Market incompleteness and the equity premium puzzle: Evidence from state-level data (SSRN Scholarly Paper No. ID 695684) Social Science Research Network, Rochester, NY.
Jacobs, K., Pallage, S., Robe, M.A., 2013. Market incompleteness and the equity premium puzzle: evidence from state-level data. J. Bank Financ. 37, 378–388. https://doi.org/10.1016/j.jbankfin.2012.09.005.
Kahsay, G.A., Osberghaus, D., 2018. Storm damage and risk preferences: panel evidence from Germany. Environ. Res. Econ. 71, 301–318. https://doi.org/10.1007/s10640-017-0152-5.
Kamstra, M.J., Kramer, L.A., Levi, M.D., Wang, T., 2014. Seasonally varying preferences: theoretical foundations for an empirical regularity. Rev. Asset Pricing Stud. 4, 39–77. https://doi.org/10.1093/rapstu/rau002.
Kidwell, D.S., Koch, T.W., Stock, D.R., 1987. Issue size and term-structure segmentation effects on regional yield differentials in the municipal bond market. J. Econ. Bus. 39, 339–347. https://doi.org/10.1016/0148-6195(87)90027-0.
Kriz, K.A., 2004. Risk aversion and the pricing of municipal bonds. Public Budget. Financ. 24, 74–87. https://doi.org/10.1111/j.0275-1100.2004.02402005.x.
Kuhnen, C.M., Knutson, B., 2011. The influence of affect on beliefs, preferences, and financial decisions. J. Financ. Quant. Anal. 46, 605–626. https://doi.org/10.1017/S0022109011000123.
Lerner, J.S., Keltner, D., 2000. Beyond valence: toward a model of emotion-specific influences on judgement and choice. Cognition Emotion 14, 473–493. https://doi.org/10.1080/026999300402763.
Liebenehm, S., Degener, N., Strobl, E., 2018. Rainfall shocks and risk aversion: Evidence from Southeast Asia (Working Paper No. WP-006) TVSEP Working Paper.
Loewenstein, G.F., Weber, E.U., Hsee, C.K., Welch, N., 2001. Risk as feelings. Psychol. Bull. 127, 267–286.
Lopes, L.L., 1987. Between hope and fear: the psychology of risk. Adv. Exp. Soc. Psychol. 20, 255–295. https://doi.org/10.1016/S0065-2601(08)60416-5.
Mehra, R., Prescott, E.C., 1985. The equity premium: a puzzle. J. Monet. Econ. 15, 145–161. https://doi.org/10.1016/0304-3932(85)90061-3.
Meyer, D.J., Meyer, J., 2005. Relative risk aversion: what do we know? J. Risk Uncertain. 31, 243–262. https://doi.org/10.1007/s11166-005-5102-x.
Neumayer, E., Barthel, F., 2011. Normalizing economic loss from natural disasters: a global analysis. Global Environ. Change 21, 13–24. https://doi.org/10.1016/j.gloenvcha.2010.10.004.
Norris, F.H., Byrne, C.M., Kaniasty, K., Diaz, E.National Center for Post-Traumatic Stress Disorder (U.S.), 2002. The range, magnitude, and duration of effects of natural and human-caused disasters: a review of the empirical literature National Center for PTSD, Vermont?.
Noy, I., DuPont, W., 2016. The long-term consequences of natural disasters — A summary of the literature SEF WORKING PAPER 02/2016, Victoria University of Wellington.
Parsley, D., Popper, H., 2018. Blue states and red states: Business cycle divergence and risk sharing Working Paper, Vanderbilt University.
Phifer, J.F., Norris, F.H., 1989. Psychological symptoms in older adults following natural disaster: nature, timing, duration, and course. J. Gerontol. 44, S207–S212. https://doi.org/10.1093/geronj/44.6.S207.
Pirinsky, C., Wang, Q., 2006. Does corporate headquarters location matter for stock returns? J. Financ. 61, 1991–2015. https://doi.org/10.1111/j.1540-6261.2006.00895.x.
Pirinsky, C.A., Wang, Q., 2011. Market segmentation and the cost of capital in a domestic market: evidence from municipal bonds. Financ. Manag. 40, 455–481. https://doi.org/10.1111/j.1755-053X.2011.01149.x.
Rabin, M., 2000. Risk aversion and expected-utility theory: a calibration theorem. Econometrica 68, 1281–1292. https://doi.org/10.1111/1468-0262.00158.
Sarkissian, S., 2003. Incomplete consumption risk sharing and currency risk premiums. Rev. Financ. Stud. 16, 983–1005. https://doi.org/10.1093/rfs/hhg019.
Savov, A., 2011. Asset pricing with garbage. J. Financ. 66, 177–201. https://doi.org/10.1111/j.1540-6261.2010.01629.x.
Schildberg-Hörisch, H., 2018. Are Risk Preferences Stable? Journal of Economic Perspectives 32, 135–154. doi:10.1257/jep.32.2.135.
Schwert, M., 2017. Municipal bond liquidity and default risk. J. Financ. 72, 1683–1722. https://doi.org/10.1111/jofi.12511.
Shiller, R.J., 1991. Arithmetic repeat sales price estimators. J. Hous. Econ. 1, 110–126. https://doi.org/10.1016/S1051-1377(05)80028-2.
Smith, V.K., 2008. Risk perceptions, optimism, and natural hazards. Risk Anal. 28, 1763–1767. https://doi.org/10.1111/j.1539-6924.2008.00880.x.
Szpiro, G.G., 1986. Measuring risk aversion: an alternative approach. Rev. Econ. Stat. 68, 156–159. https://doi.org/10.2307/1924939.
Tversky, A., Kahneman, D., 1974. Judgment under uncertainty: heuristics and biases. Science 185, 1124–1131. https://doi.org/10.1126/science.185.4157.1124.
Van den Berg, M., Fort, R., Burger, K., 2009. Natural hazards and risk aversion: Experimental evidence from latin america (2009 Conference of the International Association of Agricultural Economists No. 51394) International Association of Agricultural Economists, Beijing, China.
Vissing-Jørgensen, A., Attanasio, O.P., 2003. Stock-market participation, intertemporal substitution, and risk-aversion. Am. Econ. Rev. 93, 383–391. https://doi.org/10.1257/000282803321947399.
Wang, A.Y., Young, M., 2020. Terrorist attacks and investor risk preference: evidence from mutual fund flows. J. Financ. Econ.. https://doi.org/10.1016/j.jfineco.2020.02.008.
Wang, J., 1996. The term structure of interest rates in a pure exchange economy with heterogeneous investors. J. Financ. Econ. 41, 75–110. https://doi.org/10.1016/0304-405X(95)00854-8.
West, C.T., Lenze, D.G., 1994. Modeling the regional impact of natural disaster and recovery: a general framework and an application to Hurricane Andrew. Int. Reg. Sci. Rev. 17, 121–150. https://doi.org/10.1177/016001769401700201.