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ESSAYS ON EXTERNAL FORCES IN CAPITAL MARKETS

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ESSAYS ON EXTERNAL FORCES IN CAPITAL MARKETS

DISSERTATION

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fulfillment of the requirements for
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ABSTRACT OF DISSERTATION

ESSAYS ON EXTERNAL FORCES IN CAPITAL MARKETS

In the first chapter, I find counties more likely to be affected by climate change pay more in underwriting fees and initial yields to issue long-term municipal bonds compared to counties unlikely to be affected by climate change. This difference disappears when comparing short-term municipal bonds, implying the market prices climate change risks for long-term securities only. Higher issuance costs for climate risk counties are driven by bonds with lower credit ratings. Investor attention is a driving factor, as the difference in issuance costs on bonds issued by climate and non-climate affected counties increases after the release of the 2006 Stern Review on climate change. In the second chapter, I document the investment value of alternative data and examine how market participants react to the data's dissemination. Using satellite images of parking lots of US retailers, I find a long-short trading strategy based on growth in car count earns an alpha of 1.6% per month. I then show that, after the release of satellite data, hedge fund trades are more sensitive to growth in car count and are more profitable in affected stocks. Conversely, individual investor demand becomes less sensitive to growth in car count and less profitable in affected stocks. Further, the increase in information asymmetry between investors due to the availability of alternative data leads to a decrease in the liquidity of affected firms.

KEYWORDS: Climate change, municipal bonds, investor attention, big data, information asymmetry, liquidity

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1.1 Introduction

In this paper, I examine whether the municipal bond market prices climate change risk. The potential financial losses posed by climate change have caused growing concern among investors, with climate change being a top shareholder proposal issue in recent years.[1] For example, in Berkshire Hathaway's 2015 annual letter to shareholders, CEO Warren Buffett responded to a proxy proposal that would require Berkshire to provide an annual report on how their insurance operations are responding to the threats of climate change:

"The sponsor [of the proxy] may worry that property losses will skyrocket because of weather changes. And such worries might, in fact, be warranted if we wrote ten- or twenty-year policies at fixed prices. But insurance policies are customarily written for one year and repriced annually to reflect changing exposures. Increased possibilities of loss translate promptly into increased premiums."

While insurance companies are able to adjust to increased risks by annually repricing policies, other investments cannot be as responsive to avoid potential climate change costs. In particular, municipalities in areas that are expected to be greatly affected by sea level rise would not be able to avoid the costs associated with repairing damaged infrastructure. This leads to an important question: do investors price climate change risk when this risk cannot be easily addressed?

The municipal bond market provides a useful setting to study this question, as municipalities are unable to relocate away from climate change risk in the way a corporation could. For example, if the Folgers Coffee Company felt its New Orleans factory was at risk of being damaged by sea level rise, they could relocate the factory to a location with less climate change risk and face little financial consequence. Orleans Parish, however, cannot relocate its infrastructure and thus cannot reduce climate change risk as easily. Therefore, investors are more likely to account for climate change risk when investing in municipal bonds as opposed to corporate bonds or stocks.

Furthermore, municipal bonds are heterogeneous in term structure. This feature leads to different expected climate change risk for bonds with different maturities. Because climate induced sea level rise is likely to cause more damage in two decades compared to two years, municipal bonds with longer maturities are more likely to be affected by climate change. If investors are concerned about climate risk, then municipalities more likely to be affected by climate change (climate bonds) should face higher issuance costs for long-term bonds compared to municipalities less likely to be affected (nonclimate bonds). However, investors are unlikely to require a premium for short-term bonds issued by counties with higher climate risk.

[1] "Climate change in the 2018 US AGM season: still hot" ISS-Ethix. 2018.

To address the question of how climate change risk affects municipalities, I examine whether the cost of issuing municipal bonds is affected by the exposure a county has to climate change as measured by expected mean annual loss from sea level rise as a percentage of GDP. This measure of climate risk comes from Hallegatte, Green, Nicholls, and Corfee-Morlot (2013), who predict global losses to coastal cities based on a 40cm rise in sea level. I measure the annualized cost of issuing municipal bonds as the sum of the initial bond yield and the annualized gross spread.

I find that, on average, a one percent increase in climate risk for a county is associated with a statistically significant increase in annualized issuance costs of 23.4 basis points for long-term maturity bonds. This additional issuance cost is economically significant, as a one percent increase in climate risk is associated with an average rise in total annualized issuance costs of $1.7 million for the average county. However, when looking at short-term maturity bonds, I find no significant difference in issuance costs between climate and nonclimate bonds. The difference in issuance costs based on term structure is robust to a variety of specifications for defining long-term and short-term bonds. Moreover, placebo tests show no relation between climate risk and long-term bond issuance costs for neighboring noncoastal counties. Together, these findings suggest that investors are able to identify investments with a higher risk of being affected by climate change and that the market prices this risk.

I next examine heterogeneity in the credit ratings of municipalities. Bond rating agency Moody's recently issued a report warning coastal counties that if they are unprepared to deal with climate change damage, they will face credit downgrades.[2] The report states that Moody's expects lower rated counties to be more susceptible to climate change risks, as they generally have weaker infrastructure and smaller fiscal capacity. Bond ratings affect the prices of municipal bonds, as investors rely on them to assess credit risk (Cornaggia, Cornaggia, and Israelsen, 2017). Additionally, ratings have important effects on local economies. Adelino, Cunha, and Ferreira (2017) find that local government expenditures and employment are positively related to bond ratings. If investors already price sea level rise risk into their municipal bond investments (especially for poorly rated bonds), then Moody's downgrades could create an unnecessary burden for climate affected counties.

My results show that investors recognize that poorly rated bonds are more susceptible to climate change risk, as the significant difference in issuance costs between climate and nonclimate bonds is driven by bonds with lower credit ratings (i.e., below a Standard & Poor's rating of AA- or a Moody's rating of Aa3). This result suggests the market is able to price climate change risk with regard to credit quality, raising the question as to whether the potential Moody's downgrades based on climate risk are necessary.

To further identify whether investors are taking climate change risks into account, I conduct a quasi-natural experiment comparing issuance costs before and after a significant event related to climate change that affects whether investors pay attention to this risk. In the experiment, I examine the release of Nicholas Stern's "Economics of climate change" Review (Stern, 2008), a widely discussed report released in 2006

[2] "Moody's warns cities to address climate risks or face downgrades" Bloomberg. November 2017.

that emphasizes the potential irreversible damages climate change may cause if it is not addressed. Before the release of the Stern Review, I find no significant difference in the total annualized cost of issuance between climate and nonclimate bonds. However, after the release of the Stern Review, the difference in total annualized cost of issuing long-term climate bonds versus long-term nonclimate bonds increases significantly. Short-term bond issuance costs are unaffected by the release of the Stern Review. These results suggest that investors became more aware of climate change risks after the release of the Stern Review and began pricing these risks into their investments.

Little is known about how long-term climate change risk is priced in financial markets. Hong, Li, and Xu (2017) focus on climate change induced drought and find that markets underreact to this risk. However, Bansal, Kiku, and Ochoa (2016) find that climate change risk as proxied by temperature rise has a negative impact on asset valuations, implying markets do price climate change risk. In the real estate market, Bernstein, Gustafson, and Lewis (2017) find that homes exposed to sea level rise sell at a discount relative to otherwise similar unexposed homes. My findings contribute to the evidence that the market does react to climate change risks. Further, my results suggest that investor attention is an important factor regarding whether climate change risk is priced, as municipal bond investors do not start pricing climate risk until after the release of the Stern Review. Notably, the debate over the existence of climate change is irrelevant to my findings. Rather, the results suggest that investors require a premium for the increased uncertainty as to whether they will see a return of capital from investments in municipalities with climate risk, regardless of whether the risk is actually realized.

This paper also contributes to the literature that studies the financial consequences of climate change. Financial consequences of climate change come in four general forms: production risk, reputation risk, regulatory/litigation risk, and physical risk. Hong et al. (2017) show that production risk from prolonged droughts forecasts a negative effect on the stock returns of firms in the food industry. Dell, Jones, and Olken (2012) find that higher temperatures can reduce agricultural and industrial output. Chava (2014) shows that investors require a higher cost of capital for firms excluded by environmental screens. These firms either face the reputation risk of being labeled contributors to climate change or face regulatory risk because current output could be negatively affected by future climate change related regulation. Bernstein et al. (2017) show that the physical risk of sea level rise negatively affects the price of exposed homes. However, they find little evidence that prices are affected by sea level rise when the housing market is particularly liquid. My findings add to this literature by showing that investors are concerned about the physical risk of climate change on assets traded in a liquid market and that these investors subsequently price in this risk on the assets they hold.

Finally, this paper adds to the literature on the determinants of municipal bond issuance costs. Relevant factors for issuance costs include market transparency (Schultz, 2012), the location of the bond underwriter (Butler, 2008), credit rating (Cornaggia et al., 2017), and local government policy (Gao, Lee, and Murphy, 2017). To my knowledge, this paper is the first to provide empirical evidence of the effects of climate change on bond markets and local government financing.

1.2 Municipal bonds and issuance costs

Municipal bonds are debt issued by state or local governments, typically for the purpose of funding public projects like roads, buildings, utilities, or other infrastructure. This debt is then paid back by the municipality using either tax revenue (i.e., general obligation bonds) or other sources of revenue that come from the project (i.e., revenue bonds). For example, a bond issued to fund the building of a parking garage could then be paid back using the revenue from selling parking passes to the garage. General obligation bonds are seen as less risky because municipalities are able to raise taxes in the event that there is not enough funds to pay all debtholders.

When municipalities issue debt, they employ underwriters to structure the deal and to sell the bonds to investors. Underwriters are compensated by what is referred to as the gross spread. The gross spread is the difference in price between what the underwriters pay to buy the bonds from the municipality and what they earn when they sell the bonds to the market, assuming the bonds are sold at issue price. If the bonds are sold at a higher price than the issue price, the underwriter's total profit increases, and vice versa. A higher gross spread indicates higher search costs for the underwriter to complete the issuance.

Gross spread is a common proxy for the demand for debt in finance literature. Dougal, Gao, Mayew, and Parsons (2018) use gross spreads to determine the difference in demand for bonds issued by historically black colleges and nonhistorically black colleges. Butler (2008) uses gross spreads to show that local investment banks are better suited to issue high-risk and nonrated bonds.

Once the municipality and underwriter agree on a gross spread, the underwriter then issues the bonds to the market at the highest price (lowest yield) they can while still selling the entire bond issue. Therefore, the yield at issuance of a bond also informs us as to how much demand a particular bond issue is receiving. I measure the total annualized cost to issue a bond as the annualized gross spread of a bond plus the bond yield. It is necessary to annualize gross spread into equivalent payments over the life of a bond because gross spread is a one-time payment, whereas yield is an annual cost. I annualize gross spread by taking the geometric average of gross spread scaled by the bond's maximum maturity at issuance.

If investors see climate change as a potential risk of investment, then underwriters would have higher search costs when marketing a bond issuance, and investors would require a higher yield to compensate for the additional risk. This leads to the main hypothesis of the paper: municipal bonds with higher exposure to climate change risk will have higher issuance costs, on average.

1.3 County rankings on climate change exposure

This paper focuses on climate change risk stemming from climate-induced sea level rise. Though there are several forms of climate change risk (e.g., extreme precipitation, extreme drought, and urban heat islands), sea level rise is one of the most significant risks and the risk most studied by climatologists. The main variable I use to measure climate change risk, the mean annual loss as a percentage of GDP, comes from a study by Hallegatte et al. (2013) that predicts global losses based on a 40cm rise in sea level and assuming cities attempt to adapt to the rise in sea level (e.g., upgrading dikes and sea walls). The following discussion of their specific methodology paraphrases some of the information from the supplemental file to Hallegatte et al. (2013).

Hallegatte et al. (2013) first use elevation-based geographical information systems to compute population exposure in each 50 cm "elevation layer" from the current mean sea level. They then translate the exposed population into exposed assets using estimates of the amount of capital per inhabitant. For current defense levels in coastal cities, the authors follow the methodology of Linham, Green, and Nichollas.[3] When assessing flood losses, Hallegatte et al. (2013) assume that when the water level is below the defense level for a city, the failure probability is zero, even if the water level is higher than the sea level of the city. To translate exposed assets as a function of water level into asset losses, each elevation layer is assigned one of six categories: (1) lightweight timber-framed dwellings; (2) masonry dwellings; (3) low-income country dwellings; (4) dwelling contents; (5) nonresidential structures; and (6) nonresidential content. Mean annual flood losses are then estimated using the probability of flood losses at each water level. The authors assume climate-induced sea level rise is homogeneous and that storm surge likelihood will not change due to sea level rise. The study also considers several other drivers of floods, including demographic and socioeconomic changes and human-induced subsidence.

Table 1.1 presents each US city included in Hallegatte et al. (2013), ranked by climate risk. As municipal bonds are issued at the county level, I match the ranked cities with their associated counties. Table 1.1 shows that most climate change risk is concentrated in a few counties. The city with the highest climate risk is New Orleans, LA, which is expected to have a mean annual loss to GDP of 1.48% due to sea level rise. Notably, low climate risk in percentage terms can still mean large potential losses in dollar terms. For example, although New York/Newark's climate risk is only 0.09%, they are still expected to have annual losses of over $2.1 billion.

A shortcoming of using the estimates of the Hallegatte et al. (2013) study is that I am only able to observe climate risk estimates for major coastal cities. Fortunately, the affected counties still account for a significant 15% of the total number of issuances in my sample. However, potential biases may still occur. First, it is possible to find spurious results due to the relatively small number of counties. I address this possibility by conducting placebo tests for affected counties in Section 1.5.2. Second, I assume coastal counties not measured in Hallegatte et al. (2013) have a climate risk of zero, even though these counties will likely be negatively affected by sea level rise. This assumption is not a major concern, as it biases against finding a significant result. Nevertheless, I ensure that my results are robust to the exclusion of all unobserved coastal counties.

[3] "Costs of adaptation to the effects of climate change in the world's large port cities" Work stream 2, report 14 of the AVOID programme. 2010.

1.4 Data

I obtain data on municipal bond offerings from Bloomberg. The data for new issues is restricted to bonds with issue sizes above one million dollars and that are rated by either Standard & Poor's or Moody's. Additionally, I exclude bonds for which both the gross spread and initial yield are unavailable.[4] The final sample contains 327,152 municipal issues, 50,914 of which are issued in counties with a climate risk above zero.

Table 1.2 presents the descriptive statistics for the bond data separated by climate and nonclimate bonds. The bond issues range from January 2004 to March 2017. In a univariate setting, climate counties, on average, pay 6 basis points less in gross spread and 11 basis points more in initial yield. Bonds issued by climate counties, on average, pay 3.03% in total annualized costs to issue a bond, compared to 2.95% for nonclimate counties. For climate (nonclimate) bonds, the average issue size is $13.4 ($8) million, and the average maximum maturity is 14.63 (13.57) years. Over half of the bonds (61% and 60%) in the sample have a call provision, 15% (16%) are insured, 18% (19%) have a sinking provision, 40% (49%) are general obligation bonds, and 6% (7%) are pre-refunded. The majority of the bonds are tax exempt, 85% (81%) federally exempt, and 77% (75%) state exempt. Bonds subject to the alternative minimum tax (AMT) make up 4% (3%) of the sample. AMT's tend to have higher yields that reflects the risk that they could become taxable to some investors in the future, based on changing income levels. The average underwriter issued 16,820 (14,530) bonds during the sample period.

Following Cantor and Packer (1997), I convert Standard & Poor's and Moody's rating scales into numeric form. The highest rated bonds (AAA or Aaa) are given a value of one, bonds with ratings of AA+ or Aa1 are given a value of two, and so forth. Therefore, the median sample rating of three indicates that the median rating assigned by Standard & Poor's (Moody's) is AA (Aa2). In the case where both credit agencies rate a bond, I use Standard & Poor's rating. This is because, in the past, Moody's was more likely to assign unsolicited ratings that are likely to have a downward bias.[5]

Municipalities may choose underwriters through either negotiated or competitive offerings. A negotiated offering occurs when the issuer and an underwriter come to a contractual agreement that the underwriter will have exclusive rights to distribute the issue. In a competitive offering, multiple underwriters bid for the rights to issue the bond, with the winning bid being the one with the lowest issuance cost to the municipality. Controlling for the type of underwriting procedure is important, as the type of offering is an important factor in the cost of the issue. Competitive offerings

[4] Bloomberg denotes the gross spread as the issuance discount spread and gives the following definition: "Security issuance underwriter discount costs (including spreads, takedown, and underwriting fees disclosed by the underwriter in official documents accompanying the sale) expressed as a percentage of the total issued amount."

[5] Unsolicited ratings are ratings assigned by an agency that were not requested by an issuer (i.e., the issuer does not pay the rating agency to assign a rating). Unsolicited ratings have been criticized as a form of extortion, as agencies assign lower ratings when they are not hired by the issuer (Butler and Cornaggia, 2012).

tend to be less costly for the municipality when there are many bids, but negotiated offerings can be cheaper if there are few underwriter bids (Kidwell and Sorensen, 1983). The new issuance sample consists of 23% (28%) competitive and 77% (72%) negotiated offerings.

Municipalities often employ underwriters to issue multiple bonds in one package. Bonds included in a package tend to have a similar purpose (i.e., each bond is issued to fund the same project) but will differ in characteristics like maturity. Each maturity is assigned a separate CUSIP that is used as an identifier for trading on the secondary market. The mean (median) packaged issue for climate bonds has 12.77 (10) CUSIPs, while the mean (median) packaged issue for nonclimate bonds has 10.81 (9) CUSIPs.

Panel B of Table 1.2 details the total annualized issuance cost, yield, gross spread, and percentage of climate bonds broken down by maximum maturity and rating. The main identification strategy I use to identify long-term versus short-term bonds is whether or not the bond's maximum possible maturity is above or below 25 years. Bonds with a maximum maturity of 25 years or greater at issuance make up nearly 10% of the sample. Assuming investors are rational, I expect to see higher issuance costs for long-term climate bonds compared to long-term nonclimate bonds but no significant difference between short-term bonds. Climate change studies differ in their forecasts for when sea level rise will significantly damage coastal areas, ranging from as early as 2030 until past 2100 (Tol, 2009). To ensure that my results are not unique to the 25 year sample split, I confirm that my results are robust to a variety of term structure cutoffs in Section 1.5.2. The average total annualized cost is 4.66% for bonds with a maturity of 25 years or more and 2.82% for bonds with a maturity of less than 25 years.

Although there are relatively few counties with an observed climate risk, they represent a significant portion of the sample. This is likely because counties with an identified climate risk are among the largest in the country and therefore need to issue proportionally more bonds to fund their operations. The percentage of climate bonds in each subcategory (12.5% to 19.8%) is consistently close to the percentage of climate bonds in the total sample (15.1%). As expected, the last four rows of Panel B show that total annualized issuance cost, yield, and gross spread all increase monotonically as ratings decline.

1.5 The effect of sea level rise on municipal bond issuance costs

To examine the effects of an increase in climate risk on the cost to issue a municipal bond, I estimate the following model:

$$\begin{aligned} Total\ annualized\ issuance\ cost = \beta_1 * Climate\ risk + \beta_2 * Bond\ controls\ + \\ \beta_3 * State \times Year\ FE + \epsilon. \end{aligned} \tag{1.1}$$

Following the municipal bond literature, I include controls for the log of the issue size, the log of the maximum maturity, the bond's initial credit rating, the log of the number of CUSIPS packaged in the same issue, the log of the number of underwriter deals that the bond's underwriter has issued in the sample, and indicator variables for whether the bond is callable, insured, sinkable, pre-refunded, funded by general obligation, competitively issued, federally tax-exempt, state tax-exempt, or subject to AMT. I also include state-year fixed effects. The fixed effects control for the possibility that climate affected counties tend to issue bonds when issuance costs are relatively high as well as the possibility that the climate risk measure captures unobserved cross-state factors. All standard errors are clustered by the county of issuance, as the residuals of the regressions could be correlated within counties.

1.5.1 Main results

Table 1.3 presents the results for the effect of climate risk on issuance costs. Panel A compares results for total annualized issuance costs for long-term and short-term bonds, based on whether their maximum maturity is greater than or less than 25 years. The first three columns show that long-term bonds are more costly to issue when there is an increased risk of sea level rise for a county. Column 1 shows the relation between climate risk and total issuance cost when controlling for three primary determinants of issuance costs: the size, maturity, and credit rating of the bond. Under this specification, a one percent increase in climate risk is associated with a 33.3 basis point increase in the total annualized issuance cost of a bond, significant at the 1% level. Given the unconditional average cost of a long-term issuance is 4.66%, this represents a 7.1% increase from the mean annualized issuance cost. Similar to other findings in the municipal bond offering literature, I find that issuance costs are higher for bond issuances of smaller size, longer maturity, and a worse credit rating.[6]

In column 2, I add the rest of the controls for bond issuance characteristics that can affect issuance costs. Climate risk remains a significant factor for issuance costs, as a one percent increase in climate risk is associated with a 23.4 basis point increase in total annualized cost. This represents a 5.0% increase from the mean annualized issuance cost. In economic terms, a one percent increase in climate risk would increase the total annualized cost of issuing a long-term bond of average size ($27.5 million) by $64,350. The average county issues 26.32 long-term bonds during the sample period, bringing the total burden of a one percent increase in climate risk to an additional $1,693,692 in annualized issuance costs for the average municipality.

The final three columns of Table 1.3, Panel A present results for short-term bond issuances. The magnitude for climate risk is reduced to between 7.7 and 9.3 basis points and is insignificant in all specifications. This loss of significance is particularly striking when considering that the sample of short-term bonds is nearly 12 times larger than the sample for long-term bonds.

Panels B and C of Table 1.3 break down total annualized issuance cost into its components of initial yield and gross spread. Columns 1 and 2 of Panel B show that investors require between a 16 and 20 basis point higher yield to invest in a long-term bond with a one percent higher climate risk. For short-term bonds, the magnitude on climate risk is reduced to between 7 and 7.9 basis points and is insignificant in both

[6] Recall that rating was converted to a numeric scale. Therefore, a higher numeric rating represents a lower credit rating. In unreported tests, I substitute the rating control with rating fixed effects and find qualitatively similar results.

specifications. Panel C shows that underwriters also require a higher compensation to issue municipal bonds with climate risk. A one percent increase in climate risk is associated with between a 10.8 and 15.1 basis point increase in gross spread for long-term bonds. Climate risk once again does not appear to be a factor for short-term bonds, with an insignificant coefficient between -0.4 and 1.9 basis points.[7]

One possible concern when interpreting the climate risk coefficient is the possibility that a few counties with relatively high climate risk are driving the results. I address this concern in two ways. First, I log-transform climate risk to reduce the influence of outlying counties. Under this specification, the coefficient on climate risk remains significant at the 5% level, with a magnitude of 0.339. I use the log of climate risk in all subsequent tests to ensure that outliers in terms of climate risk are not driving the results. Second, because New Orleans is an outlier in terms of climate risk, I drop all observations of municipal issuances in Orleans Parish and reestimate the model in Eq. 1.1. The results using the sample with Orleans Parish excluded are shown in the first two columns in Panel A of Table 1.4. Climate risk (log of climate risk) is still a significant predictor of annualized issuance costs under this specification, with a significant coefficient of 0.379 (0.441). These results imply that the effect of climate risk on issuance costs is not driven by risk factors specific to New Orleans.

I next examine the relation between climate risk and issuance costs with all "unobserved" coastal counties omitted. In the main specification, I assume that all cities that were not measured by Hallegatte et al. (2013) have a climate risk of zero. This assumption should bias against finding significant results, as these unobserved coastal counties likely do have risks associated with sea level rise. Indeed, I find a stronger association between climate risk and annualized issuance costs when unobserved counties are dropped. Columns 3 and 4 in Panel A of Table 1.4 report the results. I find a coefficient on climate risk (log of climate risk) of 0.366 (0.414), which is 56% (22%) higher than the coefficient of 0.234 (0.339) in the main specification. Insignificant results are once again found for short-term issuances when estimating the model with Orleans Parish dropped and with unobserved coastal counties dropped. Together, the evidence in Tables 1.3 and 1.4 suggest investors and underwriters require a premium to accept climate change risk, and this premium varies based on the magnitude and time horizon of climate risk.

1.5.2 Robustness analyses

Even after controlling for observables in a multivariate regression, there still exist potential concerns regarding whether the results in Table 1.3 are precisely identifying the effect of climate risk on municipal offering costs. One possible concern is that the choice of the term structure cutoff does not identify what an investor would see as the cutoff for short-term and long-term bonds. Another possibility is that the small number of climate risk counties is creating a spurious result and not actually identifying climate risk. In this section, I attempt to mitigate these concerns.

[7]In the interest of parsimony, for subsequent tests I report results for the annualized total cost measure only. Results for the separate analyses of yields and gross spreads can be found in the appendix.

To ensure that investors do take into account the time horizon factor of climate risk, I conduct several robustness tests in which I vary the definition of long-term versus short-term bonds. I first test whether the results still hold when long-term (short-term) bonds are identified as those with a maturity of 20 or more (less than 20) years. I repeat this test using a cutoff of 30 years as well as varying the maximum maturity date to be 2036, 2041, or 2046. The choice to use a date as the cutoff in addition to maximum maturity at issuance is to account for the possibility that investors see climate change risk being more likely after a certain target date that may have been referenced in the media or a scientific study. The years 2036, 2041, and 2046 were chosen as they are 20, 25, and 30 years after the final full year of data in my sample, respectively.

Table 1.5 presents the results for the varying term structure splits. Panel A shows that, regardless of specification, climate risk is significantly related to the total annualized issuance cost of long-term municipal bonds. Further, the coefficient on the log of climate risk monotonically increases with the length of the term structure cutoff point. For the shortest cutoffs, the 20 year and 2036 splits, the magnitude on the log of climate risk is 19.8 and 20.5 basis points, respectively. For the longest cutoffs, the 30 year and 2046 splits, the coefficients for climate risk increase to 65.6 and 154 basis points, respectively. Panel B reports the results for the various short-term specifications. Consistent with the main results, investors do not require a premium for climate risk when the bonds mature earlier. Across all specifications, the coefficient on the log of climate risk is insignificant and smaller in magnitude compared to its long-term counterpart.[8] These results support the argument that investors require a higher premium for climate change risk when the time horizon of the investment is longer.

I next address the possibility that the small number of climate risk counties is creating spurious results by conducting two placebo tests using counties unlikely to be affected by sea level rise. In the first test, I identify placebo counties geographically, assigning the climate risk of a county to the closest noncoastal county. The placebo counties are likely to experience similar economic conditions compared to the climate affected counties. Therefore, a significant coefficient on climate risk in the placebo test would suggest the climate risk measure is identifying unobserved local traits rather than risk due to sea level rise. However, an insignificant coefficient on climate risk would suggest the measure is accurately identifying climate risk.

In the second test, I identify placebo counties by conducting a nearest neighbor matching test based on the propensity to be a climate affected county. I match to the nearest neighbor based on the size of issuances, the number of CUSIPs per issue, the total number of issues by the county in the sample, and credit rating. These variables are used to identify counties with similar sized economies and fiscal capacities. I require all matched counties to be in noncoastal states to reduce any likelihood that these counties would be affected by sea level rise. I then assign the climate risk of affected counties to their nearest neighbor matched counties and test

[8]Results are qualitatively similar for the specifications with New Orleans dropped and with unobserved coastal counties dropped (see Table A.1).

the main model specification on the placebo bonds. An insignificant coefficient on climate risk for this placebo test would suggest that the main results are correctly identifying the relation between climate risk and issuance costs.

Table 1.6 presents the results of the placebo tests. I include results for all term structure cutoffs. Panel A presents results for the test using the closest noncoastal neighbors as placebo counties. The coefficient on the log of climate risk is insignificant across all specifications, implying that unobserved local conditions are not driving the main result. Panel B shows results using the nearest neighbor matching placebo test. Again, the coefficient on the log of climate risk is insignificant in all tests, implying that the results for the actual climate affected counties are not spurious. Together, these robustness tests provide evidence that climate risk and term structure are accurately identified and suggest a causal link between climate risk and municipal bond issuance costs.

1.5.3 Credit rating split

Moody's recent report detailing how they will assess the credit impact of climate change risk mentions varied expectations for how counties with different credit ratings will adapt to these risks:

"Higher rated sovereigns tend to be less susceptible to climate change risks, since they generally have more diversified economies, stronger infrastructure and a greater ability to carry a higher debt burden at more affordable interest rates. In contrast, sovereigns with a greater reliance on agriculture, lower incomes, weaker infrastructure quality, and smaller fiscal capacity exhibit greater susceptibility to the physical effects of climate change."

The ability to carry a higher debt burden is of particular importance. Though the Federal Emergency Management Agency (FEMA) will likely assist with some of the costs of damages due to sea level rise, affected counties will still be expected to pay for a significant portion of the expenses.[9] Additionally, aid from FEMA takes time to be approved and disbursed, requiring municipalities to cover the costs of repair until federal assistance arrives. Covering disaster costs will be especially difficult for municipalities whose finances are already under pressure, as the flooding could lead to lost tax revenues, either through lost revenue from unusable infrastructure or through a shrinking population that would erode the taxable base.[10] Therefore, counties with more financial flexibility will be better able to deal with the expected damages of sea level rise. If investors recognize this heterogeneity in financial flexibility, then the increase in issuance costs for climate affected municipal bonds should be driven by counties in poorer financial health. Further, if the market already recognizes the asymmetric effect of climate risk on lower rated municipal bonds, then Moody's potential downgrades may not be necessary.

To test whether the risk premium that investors and underwriters require for climate change differs based on credit quality, I split the sample based on whether

[9] After a state of emergency is declared, FEMA provides supplemental assistance for state and local government recovery costs, with the federal share being at least 75% of eligible expenses.

[10] "Do hurricanes pose a risk to the muni bond market?" Charles Schwab. September 2017.

the issuance has a "high grade" or better credit rating. Bonds with a credit rating of AA- (Aa3 for Moody's ratings) or higher are considered high grade. High grade rated bonds make up 27% of long-term issuances and 17% of short-term issuances. Counties that issue high grade rated bonds are more likely to have stronger infrastructure and fiscal capacity and therefore should have less climate change risk. Therefore, a significant coefficient on climate risk for bonds rated below high grade and an insignificant coefficient for high grade bonds would suggest that the market accounts for differences in credit quality when assessing climate risk.

The results are shown in Table 1.7. Consistent with the market recognizing the asymmetric effect of climate risk based on credit, the coefficient on climate risk is significant only for long-term bonds that are rated below high grade. Column 1 reports that a one percent increase in climate risk is associated with a 52.7 basis point increase in the annualized costs to issue a long-term municipal bond that is rated below AA- (Aa3 for Moody's). In contrast, column 2 reports no significant relation between climate risk and annualized issuance costs for long-term municipal bonds that are high grade rated. In columns 3 and 4, I repeat the subsample tests for short-term bonds. As expected, there is no relation between climate risk and annualized issuance costs for short-term bonds, regardless of credit rating.

Standard & Poor's Global Ratings definition states that their rating system "takes into consideration the creditworthiness of insurers"; therefore, whether or not a bond is insured is accounted for in the rating split tests. The results are also robust to the exclusion of uninsured bonds from the sample. Additionally, the significant relation between climate risk and issuance costs for lower rated bonds is robust to several different credit rating splits. In unreported tests, I find the coefficient on climate risk is positive and significant when looking at long-term bonds rated below AAA, AA+, or AA. Likewise, the climate risk coefficient is insignificant when looking at long-term bonds rated AAA, AA+ or higher, or AA or higher. These results are relevant to credit rating agencies deciding how to address climate change risk, as the findings suggest the market is able to recognize the heterogeneous effects of climate change due to credit quality.

1.6 Difference-in-differences around the Stern Review

In this section, I examine whether investor attention plays a role in the pricing of climate change risks. Investor attention has been shown to be a significant factor for stock price volatility (Andrei and Hasler, 2014), short-term stock returns (Da, Engelberg, and Gao, 2011; Lou, 2014), and reactions to earnings announcements (Hirshleifer, Lim, and Teoh, 2011), among others. In the context of this paper, I expect market attention to be a key driver of whether climate risks are priced in the municipal bond market. To identify market attention on climate change, I conduct a quasi-natural experiment surrounding the release of the Stern Review, which is likely to significantly increase the market's attention toward climate change.

On October 30, 2006, economist Nicholas Stern published a report detailing the costs of damages that climate change is expected to have on the world economy. The "Stern Review" is one of the earliest and most thorough analyses of the economics of climate change and also one of the most well known. After the release of the Stern Review, it is likely that investors began paying attention to the risks climate change poses on their investments.

An increase in attention to climate change after the release of the Stern Review is evident when examining Google search volume. Fig. 1 plots the quarterly average search volume for the term "climate change" for 2005 to 2007. Search volume for climate change spikes following the release of the Stern Review and is higher for all quarters after the release relative to the quarters before. This rise in search volume suggests an increased attention toward the risks of climate change after the Stern Review's release.

Additionally, Stephen Kass and Jean McCarroll cite the Stern Review when making the following prediction about municipal markets:[11]

"National and municipal governments around the world will be called on not only to deal with short-term floods and evacuees, but to provide emergency food, water and health care services, and to undertake agricultural restoration and large-scale urban reconstruction... Insurance companies, investors and lending institutions will, after the initial losses, begin to introduce (as some insurers already are) screening standards designed to identify climate change risks."

Other references in the press to the Stern Review state the review raised awareness to climate change for "Wall Street investors, insurance executives, state treasurers and pension fund managers"[12] and increased voter attention toward environmentally conscious politicians.[13] The Stern Review is unlikely to change the risk profile of municipal bonds other than through increased awareness of climate change risk. Therefore, a significant increase in issuance costs for long-term climate bonds after the Stern Review would indicate that the measure of climate change is identifying climate risk and that investor attention is a key determinant of whether the market prices climate change.

In Table 1.8, I conduct difference-in-differences tests to examine whether increased investor attention on climate change translates into higher annualized issuance costs for climate affected bonds. I create an indicator variable equal to zero if the bond was issued prior to the release of the Stern Review and equal to one after the Stern Review's release. The interaction variable *Ln(Climate risk)* $\times$ *Stern* will give the marginal effect of the Stern Review on the annualized issuance costs of climate bonds relative to nonclimate bonds.

The results indicate that the difference in annualized issuance costs between climate and nonclimate bonds does increase after the release of the Stern Review. Column 1 of Table 1.8 presents results for the difference-in-differences tests for long-term bonds. Prior to the release of the Stern Review, there is no significant relation between climate risk and annualized issuance costs, as the coefficient on climate risk is an insignificant -15.9 basis points. However, the market begins pricing climate risk after the release of the Stern Review, with a coefficient on the interaction term of

[11] "Climate change and environmental practice" New York Law Journal. 2006

[12] "Wall Street eyes heart of darkness: global warming" Reuters. December 2006.

[13] "Climate change catching voter attention around world" Reuters. January 2007.

60.7 basis points, significant at the 5% level.

To isolate the effect of market attention on the pricing of climate risk, I restrict the sample to bonds issued near the release of the Stern Review. I examine two time frames around the Stern Review: a two-year window (one year before and after the Stern Review) and a one-year window (six months before and after the Stern Review). The narrower time frames help mitigate the possibility of preexisting trends confounding the results. Looking first at the two-year window in column 2, the interaction term remains statistically significant with a coefficient of 63.3 basis points. For the one-year window, the interaction term is reduced to 38.4 basis points and is statistically insignificant (t-statistic = 1.3). The similar magnitude of the coefficients for the full sample and the shortened time frames suggests that most of the effect occurs in the year after the release of the Stern Review.[14]

In Fig. 2, I further examine how the premium required for climate affected bonds changes around the Stern Review. The figure shows the difference in annualized issuance costs based on climate risk for the five quarters before and after the release of the Stern Review (which was released in the fourth quarter of 2006). The difference in annualized issuance costs is near zero in the five quarters preceding the Stern Review and grows considerably after the review is released. This difference continues to grow for several quarters after the event and is statistically significant by the third quarter of 2007, suggesting the market gradually incorporated the information provided by the Stern Review. The change in trends shown in Fig. 2 is consistent with market attention being a driving factor in whether climate risk is priced.

In the final three columns of Table 1.8, I examine whether the Stern Review had any impact on short-term bond issuances. The coefficients on the interaction terms for all specifications are insignificant and greatly reduced compared to the long-term bonds. For the full sample, the interaction term is an insignificant 0.1 basis points. The results in Table 1.8 and Fig. 2 suggest that investors began paying more attention to the risks of climate change after the release of the Stern Review and recognized that these risks would be concentrated in long-term bond issuances.

1.7 Conclusion

The impact that climate change risk has on the municipal bond market is meaningful. I find that long-term municipal bonds are significantly affected by their level of exposure to climate change risk, whereas short-term bonds do not appear to be affected. This finding is robust to numerous term structure specifications. Additionally, the results suggest the market accounts for differences in credit quality when assessing climate risk. Finally, I find that investors appear to react to climate change news, showing that climate change is on the forefront of factors influencing investors' decisions.

[14] In Table A.6 of the appendix, I confirm that the results of the Stern Review difference-in-differences tests are robust to the exclusion of bonds issued in New Orleans and bonds issued in unobserved coastal counties.

For the purposes of this paper, the debate over the existence of climate change is irrelevant. Many forms of investment risk go unrealized, yet investors require a premium for the uncertainty that accompanies those risks. The findings in this paper suggest that investors account for the increased uncertainty as to whether they will see a return of capital from municipal bonds issued in counties with higher climate change risk, regardless of whether those counties will actually be affected by climate change.

The evidence found in this study has important implications for the counties most likely to be affected by climate change. Because climate change risk is causing counties to be negatively affected today through higher debt issuance costs, these counties should be proactive in reducing the amount of damage that sea level rise is likely to cause to their municipalities. The findings in this paper provide evidence that investors are aware of climate change risks to their assets and are taking these risks into account when investing. The ability of the market to recognize differences in climate risk based on credit quality is an important factor for whether credit rating agencies decide to downgrade these municipalities' bonds.

Though there has been prior research showing that investors account for reputation and regulation risk when investing in companies that contribute to climate change, this paper is the first to document that investors account for the risk that climate change poses on fixed income assets in their portfolios. The results of this paper could potentially motivate counties to take steps toward preparing themselves for the potential damages of sea level rise, helping them to avoid climate change's "inconvenient cost."

Table 1.1: Counties with climate change risk

This table ranks cities by their exposure to climate change risk by expected mean annual loss as a percentage of a city's GDP. The mean annual loss is the optimistic bound calculated assuming a 40cm rise in sea level and that cities attempt to adapt to the rise in sea level. Cities and counties that are grouped together are assigned the same climate risk. The estimates in this table are from Hallegatte et al. (2013). All counties not included in this table are assigned a climate risk of zero.

City	County	Mean annual loss (MM$)	Climate risk
New Orleans, LA	Orleans	1940	1.479%
Miami, FL	Miami Dade	2964	0.420%
Tampa/St. Petersburg, FL	Hillsborough, Pinellas	948	0.324%
Virginia Beach, VA	Virginia Beach	328	0.173%
Boston, MA	Suffolk	849	0.149%
Baltimore, MD	Baltimore	299	0.104%
LA/Long Beach/Santa Ana, CA	Los Angeles, Orange	217	0.097%
New York, NY/ Newark,NJ	Bronx, Kings, New York, Queens, Richmond, Essex	2159	0.089%
Providence, RI	Providence	135	0.083%
Philadelphia, PA	Philadelphia	309	0.044%
San Francisco/Oakland, CA	San Francisco, Alameda	185	0.042%
Houston, TX	Walker, Montgomery, Liberty, Waller, Austin, Harris, Chambers, Colorado, Wharton, Fort Bend, Galveston, Brazoria, Matagorda	214	0.038%
Seattle, WA	King	90	0.023%
Washington D.C.	Washington	91	0.016%
San Diego, CA	San Diego	14	0.004%
Portland, OR	Multnomah	4	0.002%
San Jose, CA	Santa Clara	2	0.001%

Table 1.2: New issue municipal bond data

This table reports descriptive statistics for the sample of bonds acquired from Bloomberg, covering bonds that were issued from January 2004 through March 2017. All bonds in this sample have issue sizes of $1MM or greater and are rated by either S&P or Moody's. Panel A reports variables including the difference between the price underwriters paid for the issue and what price they sold the issue to the market (Gross spread, winsorized at 3% and 97%); the yield the bond was issued at (winsorized at 3% and 97%); the total annualized cost of issuance (annualized gross spread plus yield); the total size of the issue (Issue size); the bond's maturity not considering options of the issue (Max maturity); dummy variables equaling one if the bond is callable, insured, sinkable, GO backed, pre-refunded, or competitively issued; a numerical scale of credit rating (Rating); and dummy variables identifying whether the bond is exempt from federal and state taxes. AMT identifies bonds that are subject to the alternative minimum tax. CUSIPS/Issue reports how many bonds are packaged in each issue and # of deals an underwriter has issued in the sample. Panel B breaks down the statistics by the time range the bond was issued and by rating. Each row presents the mean value for each variable. N denotes the number of observations for each category that have nonmissing values of total annualized issuance cost.

Panel A: Descriptive statistics by climate risk

		Climate bonds				Nonclimate bonds		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	N	Mean	Median	SD	N	Mean	Median	SD
Total annualized cost (%)	40161	3.03	2.93	1.52	210695	2.95	2.85	2.17
Gross spread (%)	41766	0.54	0.49	0.30	217113	0.60	0.53	0.33
Yield (%)	49309	3.02	3.00	1.42	269820	2.91	2.85	1.37
Issue size (MM$)	50914	13.40	4.36	33.40	276238	8.00	2.62	22.20
Max maturity (Years)	50914	14.63	13.98	8.65	276238	13.57	12.54	8.10
Callable	50914	0.61	1.00	0.49	276238	0.60	1.00	0.49
Insurance	50914	0.15	0.00	0.36	276238	0.16	0.00	0.37
Rating	50914	3.25	3.00	1.90	276238	3.22	3.00	1.91
Sinkable	50914	0.18	0.00	0.39	276238	0.19	0.00	0.39
GO	50914	0.40	0.00	0.49	276238	0.49	0.00	0.50
Pre-refunded	50914	0.06	0.00	0.24	276238	0.07	0.00	0.25
Competitive	50914	0.23	0.00	0.42	276238	0.28	0.00	0.45
AMT	50914	0.04	0.00	0.20	276238	0.03	0.00	0.17
Fed exempt	50914	0.85	1.00	0.36	276238	0.81	1.00	0.39
State exempt	50914	0.77	1.00	0.42	276238	0.75	1.00	0.43
CUSIPS/Issue	50914	12.77	10.00	10.38	276238	10.81	9.00	8.83
# Underwriter deals (M)	50914	16.82	17.95	10.75	276238	14.53	15.92	10.62

Panel B: Descriptive statistics by categories

	(1) Total cost	(2) Yield	(3) Spread	(4) % Climate	(5) N
Max maturity $\geq$ 25	4.66	4.58	0.67	19.78%	19527
Max maturity $<$ 25	2.82	2.77	0.59	15.10%	231280
Rating = 1	2.62	2.63	0.52	14.53%	46544
Rating = 2, 3, or 4	2.92	2.90	0.61	16.45%	155131
Rating = 5, 6, or 7	3.27	3.31	0.62	12.48%	39869
Rating $\geq$ 8	4.20	4.09	0.91	18.70%	9312

Table 1.3: Effect of climate risk on municipal bond annualized issuance costs

This table presents the results of ordinary least squares regressions of Eq. (1). The variable of interest is Climate risk, defined in Table 1.1. The long-term sample contains bond issuances with a maximum maturity of 25 years or more. The short-term sample contains bond issuances with a maximum maturity of less than 25 years. The dependent variable in Panel A is the total annualized issuance cost of a municipal bond. In Panel B, the dependent variable is the initial yield of the bond. Gross spread is the dependent variable in Panel C. t-statistics, based on errors clustered by county, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Panel A: Total annualized issuance cost for long-term and short-term bonds

	Long-term			Short-term		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Total annualized cost					
Climate risk	0.333***	0.234*		0.092	0.077	
	(2.932)	(1.854)		(1.525)	(1.544)	
Ln(Climate risk)			0.339**			0.093
			(2.085)			(1.117)
Ln(Size)	-0.080***	-0.070***	-0.070***	-0.008	0.001	0.001
	(-7.863)	(-7.010)	(-7.028)	(-1.262)	(0.178)	(0.176)
Ln(Maturity)	0.813***	0.818***	0.818***	0.951***	0.667***	0.667***
	(5.666)	(6.317)	(6.307)	(21.872)	(8.230)	(8.230)
Rating	0.106***	0.116***	0.116***	0.139***	0.126***	0.126***
	(16.950)	(17.215)	(17.240)	(17.034)	(13.848)	(13.851)
Callable		0.007	0.008		0.532***	0.532***
		(0.074)	(0.078)		(6.800)	(6.800)
Insurance		0.023	0.023		0.235***	0.235***
		(0.881)	(0.880)		(12.754)	(12.764)
Sinkable		0.056	0.057		0.284***	0.284***
		(0.735)	(0.738)		(21.369)	(21.362)
GO		0.006	0.007		-0.083***	-0.083***
		(0.180)	(0.194)		(-3.800)	(-3.799)
Pre-refunded		0.105***	0.105***		0.039**	0.039**
		(4.500)	(4.498)		(1.969)	(1.971)
Competitive		-0.089	-0.089		-0.055***	-0.055***
		(-1.467)	(-1.465)		(-5.380)	(-5.368)
Fed exempt		-0.476***	-0.476***		-0.313***	-0.313***
		(-11.091)	(-11.092)		(-9.647)	(-9.649)
State exempt		0.028	0.027		-0.052*	-0.052*
		(0.451)	(0.431)		(-1.746)	(-1.746)
AMT		-0.248***	-0.248***		0.071	0.071
		(-4.464)	(-4.463)		(1.568)	(1.567)
Ln(CUSIPS/Issue)		0.171***	0.170***		-0.027*	-0.027*
		(6.309)	(6.291)		(-1.954)	(-1.953)
Ln(Underwriter deals)		-0.000	-0.000		0.000	0.000
		(-0.032)	(-0.028)		(0.005)	(0.009)
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,527	19,527	19,527	231,280	231,280	231,280
R-squared	0.284	0.295	0.295	0.268	0.284	0.284

Panel B: Yield for long-term and short-term bonds

	Long-term		Short-term	
	(1)	(2)	(3)	(4)
Dependent variable:	Yield	Yield	Yield	Yield
Climate risk	0.161**		0.070	
	(2.219)		(1.462)	
Ln(Climate risk)		0.203*		0.079
		(1.816)		(1.008)
Controls	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
Observations	27,355	27,355	291,746	291,746
R-squared	0.503	0.503	0.839	0.839

Panel C: Gross spread for long-term and short-term bonds

	Long-term		Short-term	
	(1)	(2)	(3)	(4)
Dependent variable:	Spread	Spread	Spread	Spread
Climate risk	0.108**		-0.004	
	(1.972)		(-0.072)	
Ln(Climate risk)		0.152**		0.019
		(2.188)		(0.222)
Controls	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
Observations	24,514	24,514	234,321	234,321
R-squared	0.368	0.369	0.326	0.326

Table 1.4: Effect of climate risk on municipal bond annualized issuance costs: robustness

This table presents robustness checks for the regressions reported in Table 1.3. Columns 1, 2, 5, and 6 drop all observations for bonds that were issued in Orleans Parish. Columns 3, 4, 7, and 8 also drop all observations for bonds issued in coastal counties that are not assigned a climate risk in Hallegatte et al. (2013). The dependent variable in Panel A is the total annualized issuance cost of a municipal bond. In Panel B, the dependent variable is the initial yield of the bond. Gross spread is the dependent variable in Panel C. t-statistics, based on errors clustered by county, are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Panel A: Total annualized issuance cost for long-term and short-term bonds

	Long-term				Short-term			
	No New Orleans		No unobs. coastal		No New Orleans		No unobs. coastal	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Total cost	Total cost	Total cost	Total cost	Total cost	Total cost	Total cost	Total cost
Climate risk	0.379**		0.366**		0.035		-0.035	
	(2.316)		(2.023)		(0.339)		(-0.234)	
Ln(Climate risk)		0.441**		0.414*		0.040		-0.046
		(2.250)		(1.889)		(0.324)		(-0.269)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,512	19,512	16,749	16,749	231,030	231,030	196,330	196,330
R-squared	0.295	0.295	0.274	0.274	0.283	0.283	0.252	0.252

Panel B: Yield for long-term and short-term bonds

	Long-term				Short-term			
	No New Orleans		No unobs. coastal		No New Orleans		No unobs. coastal	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Yield	Yield	Yield	Yield	Yield	Yield	Yield	Yield
Climate risk	0.249**		0.222*		0.020		-0.067	
	(1.953)		(1.645)		(0.200)		(-0.463)	
Ln(Climate risk)		0.285*		0.241		0.019		-0.084
		(1.906)		(1.503)		(0.167)		(-0.513)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,334	27,334	23,422	23,422	291,479	291,479	245,617	245,617
R-squared	0.510	0.510	0.516	0.516	0.835	0.835	0.833	0.833

Panel C: Gross spread for long-term and short-term bonds

	Long-term				Short-term			
	No New Orleans		No unobs. coastal		No New Orleans		No unobs. coastal	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Spread	Spread	Spread	Spread	Spread	Spread	Spread	Spread
Climate risk	0.192**		0.194*		0.119		0.147	
	(2.412)		(1.940)		(1.131)		(1.522)	
Ln(Climate risk)		0.220**		0.222*		0.139		0.170
		(2.405)		(1.946)		(1.131)		(1.511)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,496	24,496	21,111	21,111	234,067	234,067	199,026	199,026
R-squared	0.347	0.347	0.353	0.353	0.312	0.312	0.312	0.312

Table 1.5: Maturity

This table reports the results of ordinary least squares regressions of Eq. (1) for varying term structure specifications. The variable of interest is the log of Climate risk, defined in Table 1.1. The dependent variable is the total annualized issuance cost of a municipal bond. Panel A presents results for long-term maturity specifications. Panel B reports results for short-term maturity specifications. t-statistics, based on errors clustered by county, are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Panel A: Long-term specifications

	(1)	(2)	(3)	(4)	(5)
Issue maturity:	$\geq$ 20 Years	$\geq$ 30 Years	$\geq$ 2036	$\geq$ 2041	$\geq$ 2046
Ln(Climate risk)	0.198*	0.656**	0.205*	0.489*	1.540***
	(1.876)	(2.171)	(1.705)	(1.714)	(2.967)
Controls	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes
Observations	46,191	6,665	25,307	8,495	2,095
R-squared	0.368	0.232	0.339	0.222	0.160

Panel B: Short-term specifications

	(1)	(2)	(3)	(4)	(5)
Issue maturity:	$<$ 20 Years	$<$ 30 Years	$<$ 2036	$<$ 2041	$<$ 2046
Ln(Climate risk)	0.069	0.108	0.098	0.113	0.113
	(0.789)	(1.272)	(1.171)	(1.353)	(1.347)
Controls	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes
Observations	204,650	244,091	225,512	242,273	248,642
R-squared	0.227	0.310	0.293	0.320	0.322

Table 1.6: Placebo tests

This table presents regression results of Eq. (1) for various long-term specifications where climate risk is assigned to placebo counties. In Panel A, placebo counties are identified as the counties closest to the climate counties but not located on the coast. In Panel B, the placebo counties are assigned using nearest neighbor matching on the propensity to be a climate affected county. Neighbors are matched based on the size of issuances, the number of CUSIPs per issue, the total number of issues by the county in the sample, and credit rating. I require all matched counties to be in noncoastal states. The dependent variable is the total annualized cost to issue a municipal bond. The variable of interest is the log of Climate risk, defined in Table 1.1. t-statistics, based on errors clustered by county, are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Panel A: Geographic matching

	(1)	(2)	(3)	(4)	(5)	(6)
Issue maturity:	$\geq$ 20 Years	$\geq$ 25 Years	$\geq$ 30 Years	$\geq$ 2036	$\geq$ 2041	$\geq$ 2046
Ln(Climate risk)	-0.007	0.135	0.223	0.111	0.012	0.045
	(-0.058)	(0.738)	(0.728)	(0.825)	(0.092)	(0.107)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,191	19,527	6,665	25,307	8,495	2,095
R-squared	0.606	0.578	0.563	0.670	0.630	0.702

Panel B: Nearest neighbor matching

	(1)	(2)	(3)	(4)	(5)	(6)
Issue maturity:	$\geq$ 20 Years	$\geq$ 25 Years	$\geq$ 30 Years	$\geq$ 2036	$\geq$ 2041	$\geq$ 2046
Ln(Climate risk)	-0.061	-0.127	-0.294	-0.057	-0.151	-0.439
	(-1.083)	(-1.493)	(-1.336)	(-0.663)	(-1.197)	(-1.637)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,191	19,527	6,665	25,307	8,495	2,095
R-squared	0.606	0.578	0.563	0.670	0.630	0.703

Table 1.7: Credit rating split

This table reports the results of ordinary least squares regressions of Eq. (1) for different credit rating specifications. The variable of interest is the log of Climate risk, defined in Table 1.1. Bonds included in the "<AA-" sample have a credit rating at issuance below AA- (or below Moody's Aa3 if they are not rated by S&P). Bonds included in the "≥AA-" sample have a credit rating of AA- or higher (or Moody's Aa3 or higher if they are not rated by S&P). The long-term sample contains bond issuances with a maximum maturity of 25 years or more. The short-term sample contains bond issuances with a maximum maturity of less than 25 years. The dependent variable is the total annualized issuance cost of a municipal bond. *t*-statistics, based on errors clustered by county, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	Long-term		Short-term	
	(1)	(2)	(3)	(4)
Credit rating:	$<$ AA-	$\geq$ AA-	$<$ AA-	$\geq$ AA-
Ln(Climate risk)	0.527**	0.141	0.107	0.091
	(2.041)	(0.686)	(0.878)	(0.634)
Controls	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
Observations	5,339	14,095	43,714	187,529
R-squared	0.609	0.238	0.090	0.724

Table 1.8: Difference-in-differences of issuance costs around the Stern Review

This table presents difference-in-difference estimates for the total annualized cost to issue a municipal bond before and after the Stern Review was released. Stern takes a value of one if the bond was issued after the Stern Review was released and zero otherwise. The Stern Review was released on October 30, 2006. The long-term sample contains bond issuances with a maximum maturity of 25 years or more. The short-term sample contains bond issuances with a maximum maturity of less than 25 years. Columns 1 and 4 contain bond issuances for the entire sample. Columns 2 and 5 restrict the sample to bonds issued within a two-year window (one year before until one year after) around the Stern Review. Columns 3 and 6 restrict the sample to bonds issued within a one-year window (six months before until six months after) around the Stern Review. *t*-statistics, based on errors clustered by county, are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

	Long-term			Short-term		
	(1)	(2)	(3)	(4)	(5)	(6)
Time frame:	Full sample	Two years	One year	Full sample	Two years	One year
Ln(Climate risk)	-0.159	-0.242*	-0.205	0.091	0.533	-0.064
	(-0.727)	(-1.708)	(-1.254)	(0.228)	(1.163)	(-0.243)
Ln(Climate risk) x Stern	0.607**	0.633**	0.384	0.001	-0.554	-0.138
	(2.429)	(2.167)	(1.295)	(0.002)	(-1.250)	(-0.487)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,561	5,000	2,406	231,295	8,579	4,142
R-squared	0.297	0.220	0.248	0.284	0.124	0.156

Figure 1.1: Google search volume for “climate change” around the Stern Review

This figure presents the quarterly average search frequency for the term “climate change” using Google Trends. The search volume is scaled so that 100 represents the peak search volume for the time frame of 2005 to 2007. The vertical line indicates the release date of the Stern Review, October 30, 2006.

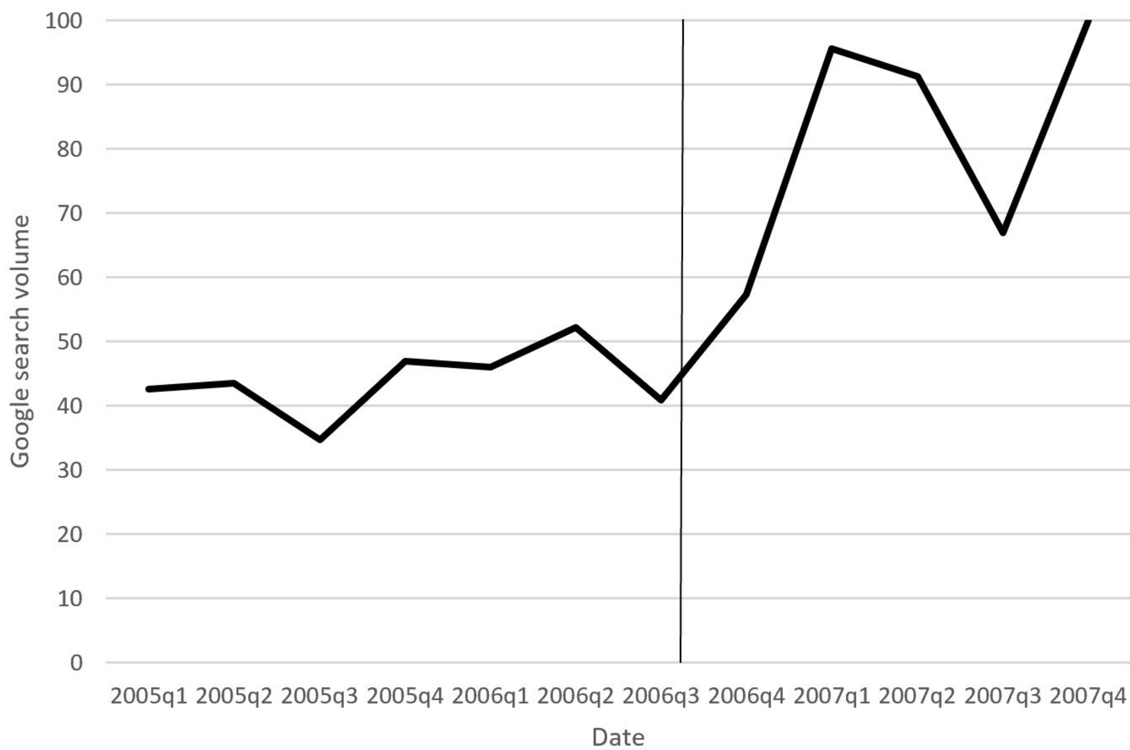
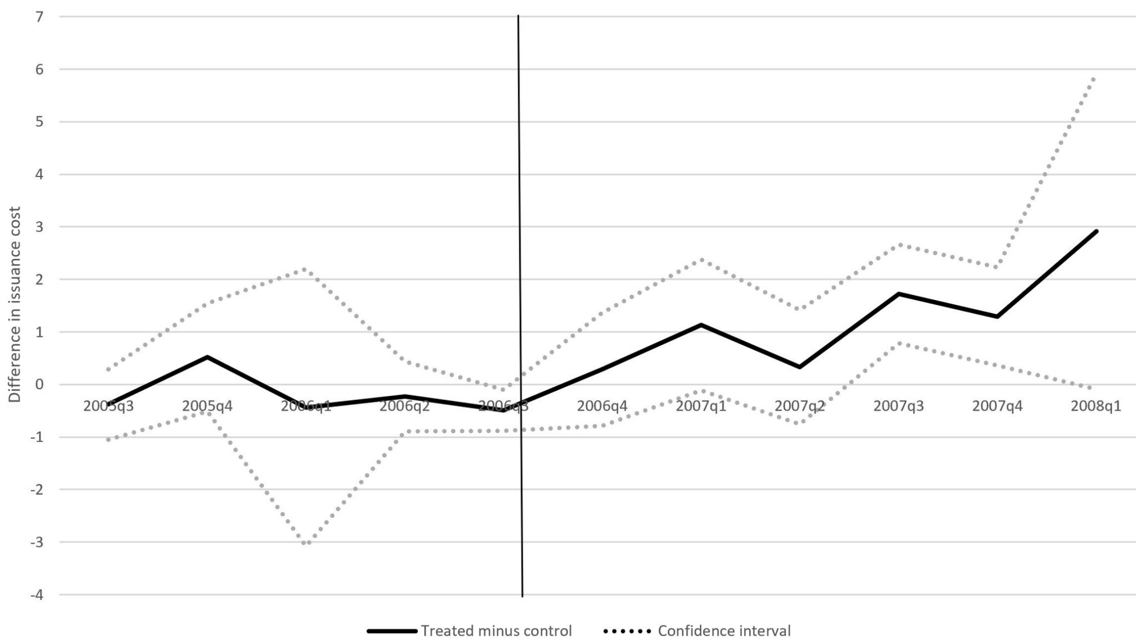


Figure 1.2: Climate risk & issuances costs around the Stern Review

This figure presents the difference in municipal bond annualized issuance costs for counties with climate risk relative to counties without climate risk around the release of the Stern Review. The coefficients are based on a regression of total annualized issuance cost on the interaction of climate risk and year-quarter time dummies. The regression also includes the full set of controls used in the main specification in Table 1.3. Ninety percent confidence intervals based on standard errors clustered by county of issuance are shown using dotted lines. Coefficients for the five quarters before and after the event are presented. The vertical line indicates the release date of the Stern Review, October 30, 2006.



Chapter 2 Unlevelling the Playing Field: the Investment Value and Capital Market Consequences of Alternative Data

> "Far from creating a level playing field, where more readily available information simply leads to greater market efficiency, the impact of the information revolution is the opposite: it is creating hard-to access realms for long-term alpha generation for those players with the scale and resources to take advantage of it."
>
> - Schroders Investment Management[1]

2.1 Introduction

The proliferation of alternative data has been one of the most striking changes to financial markets in recent years. Alternative data, also commonly referred to as big data, is any non-traditional data that can be used in the investment process.[2] As the introductory quote suggests, proponents of this information revolution believe that alternative data has the potential to uncover fundamental information before the release of more traditional information sources, such as financial statements or macroeconomic announcements. The majority of asset managers appear to share this opinion, with a recent report by JP Morgan estimating asset managers are spending \$2-3 billion annually on alternative data.[3] Further, a survey conducted by Standard & Poor's indicates 80% of asset managers plan to increase their investments in big data, with only 6% of asset managers believing big data is not important to their investment process.[4]

The exponential growth of alternative data sources has significant implications for the informational environment of the firm. The growing dissemination of alternative data may only have investment value for the small group of investors who are either able to afford early access to such information or have a comparative advantage in processing and trading on the information. In fact, survey evidence indicates the two most cited impediments to the use of alternative data are high fixed costs and lack of expertise in managing the data.[5] Therefore, the rise in alternative data creates a potential informational advantage for large sophisticated investors relative to small investors.

The goal of this study is to assess the investment value and capital market consequences of alternative data. To do so, I collect detailed data on parking lot car counts for 163 companies from 2010-2017 from Orbital Insight, a leading provider of data derived from satellite imagery. An important feature of this data is that Orbital Insight began selling the data for these companies at different points in time. Specifically, Orbital Insight began selling data for 54 companies in the summer of 2015, 41 more companies in the summer

[1] Is Big Data the Key to Bigger Investment Returns? Morningstar. February 23, 2018.

[2] Examples include social media sentiment analysis (e.g., PsychSignal), crowdsourced investment research (e.g., Seeking Alpha and Estimize), credit card transactions and consumer spending data (e.g., Yodlee and Earnest), and satellite images (e.g., Orbital Insight).

[3] "JP Morgan: Alternative Data Is Altering Investment Landscape" Integrity Research Associates. June 14, 2017.

[4] Morningstar, 2018

[5] "This is the Future of Investing, and You Probably can't Afford it" Business Insider. May 28, 2017.

of 2016, and 33 more companies at the beginning of 2017. Additionally, Orbital Insight collected car count data for 35 companies that were not released in my sample period. This staggered introduction of companies offers a relatively clean setting to explore the causal effects of the dissemination of alternative data on its investment value, its impact on the trading activities of sophisticated and individual investors, and the liquidity of affected firms.

I first demonstrate that a trading strategy based on alternative data reveals new information that predicts stock returns. I construct an investment strategy that each month goes long stocks in the top quintile of year-over-year car count growth and short stocks in the bottom quintile. This strategy generates monthly abnormal returns of 1.6% per month. This result holds in both equal-weighted and value-weighted portfolios and is robust to various risk-adjustments. I also find that an interquartile increase in quarterly car count growth is associated with a 14.47% increase in revenue surprise and a 0.17% increase in price-scaled unexpected earnings. These results suggest that growth in parking lot traffic is able to predict stock prices because it conveys important information about firms' future cash flows.

I next examine how the investment value of satellite data changes following the dissemination of the data to roughly 70 large asset management companies, most of whom are hedge fund managers. Somewhat surprisingly, I find the broader dissemination of the data has virtually no effect on the profitability of the trading strategy. Further, the profitability of the trading strategy persists even for stocks with characteristics that are associated with lower limits to arbitrage.

Given the persistent abnormal returns available from trading on alternative data, it is likely that large sophisticated investors are taking advantage of this opportunity. Hedge funds rank among the most sophisticated investors (Brunnermeier and Nagel (2004); Chen, Kelly, and Wu (2018)) and are able to execute complex trading strategies (Huang (2017); Jame (2017)). Additionally, the majority of initial clients for alternative data providers have been hedge funds.[6] Therefore, I test whether sophisticated investors are taking advantage of alternative data by analyzing the trading behavior and profitability of hedge funds around the dissemination of satellite data. Before Orbital Insight begins selling the data, I find no relation between car count growth and abnormal changes in hedge fund holdings. However, abnormal hedge fund holdings become significantly more responsive to car count growth after the data is released. This change in hedge fund trading behavior increases profitability for the funds, as abnormal hedge fund holdings in firms covered by Orbital Insight are associated with higher abnormal returns once the satellite data is disseminated.

I further investigate the trading behavior of institutional investors in relation to the use of alternative data by examining non-hedge fund asset managers (e.g., mutual funds, banks, and insurance companies). I find no significant change in the trading behavior or profitability of non-hedge fund institutions surrounding the release of the satellite data. This is unsurprising, as conversations with industry professionals and survey data both suggest that non-hedge fund institutions will be late adopters of alternative data.[7] Although these funds may be able to afford the high fees associated with alternative data, they may find it too difficult to extract accurate and timely trading signals to justify the expense.

Big data creates a challenge for the subset of investors who are either unaware of the

[6] "Alternative Data Use Cases Report" Eagle Alpha. April, 2018.

[7] "Putting Alternative Data to Use in Financial Markets" Greenwich Associates. September 12, 2017.

data or unable to take advantage of it. In particular, individual investors lack the resources to obtain and extract profitable signals from alternative data. Further, individuals investors' tendency to be contrarian traders (Grinblatt and Keloharju (2000); Kaniel, Saar, and Titman (2007)) means they are likely the liquidity suppliers for the demand created by alternative data. Consistent with smaller investors being unable to utilize alternative data, I find individual investor demand becomes negatively associated with car count growth after Orbital Insight begins selling the data. Further, individual investor demand predicts negative abnormal announcement returns once the satellite data is released.

My final tests analyze how firms are affected by the release of alternative data. The informational advantage for large sophisticated investors due to alternative data has important implications for firms' liquidity. On the one hand, the availability of alternative data reduces the information asymmetry between firm insiders and outsiders, which could enhance liquidity (Zhu, 2018). On the other hand, big data increases the information asymmetry between sophisticated investors and individual investors. In particular, theory predicts market makers may react to the the risks of dealing with informed traders by increasing bid-ask spreads (Copeland and Galai (1983); Glosten and Milgrom (1985)). Which effect dominates is ultimately an empirical question. Consistent with the rise of information asymmetry between sophisticated and individual investors being the dominant influence, I find that adverse selection arising from the availability of alternative data leads to higher bid-ask spreads and amihud illiquidity ratios for treated firms.

This paper makes several contributions to the literature. First, it contributes to the growing literature that uses big data to predict stock prices and firm fundamentals. Recent studies show that the use of textual analysis to gauge investor opinion from blogs Seeking Alpha (Chen, De, Hu, and Hwang, 2014) and Twitter (Bartov, Faurel, and Mohanram, 2016) can be used to predict future stock returns and earnings surprises. Huang (2017) uses data on product reviews from Amazon.com to show that consumer opinions contain relevant information for stock pricing and that hedge fund holdings are positively correlated with changes in product reviews. Jame, Johnston, Markov, and Wolfe (2016) find that crowdsourced forecasts from Estimize are incrementally useful in predicting earnings. Da, Engelberg, and Gao (2011) use data on search frequency from Google and find that an increase in search frequency predicts higher short-term stock prices. While prior research using data similar to Orbital Insight's satellite data finds earnings and revenue predictability (Froot, Kang, Ozik, and Sadka (2017); Zhu (2018)), my study is the first to construct a profitable monthly trading strategy based on satellite data. Additionally, this paper is the first to show that the profitability of trading strategies based on alternative data is unrelated to its broader dissemination, suggesting the alpha decay thought to be associated with the implementation of big data investment strategies may be less extreme than once expected.

Second, this paper contributes to the burgeoning literature on how alternative data impacts financial markets. Froot et al. (2017) develop a proxy for real-time corporate sales using data from mobile phones and tablets to show that managers bias earnings forecasts depending on the firm's real-time performance. Zhu (2018) argues the release of alternative datasets reduces information acquisition costs, ultimately leading to greater stock price efficiency, less insider trading, and more efficient investing by the firm's managers. My paper contributes to this literature by being the first to show that sophisticated investors (specifically, hedge funds) benefit from the dissemination of alternative data while individual investors suffer.

Third, this paper adds to the literature on asymmetric information between investors.

Looking at a reduction in information asymmetry between investors following Regulation Fair Disclosure, which disallowed the selective disclosure of material information, Chiyachantana, Jiang, Taechapiroontong, and Wood (2004) and Eleswarapu, Thompson, and Venkataraman (2004) find that stock liquidity improves following the regulation. Focusing on the rise of investment research websites, Farrell, Green, Jame, and Markov (2018) show that stocks that have reductions in coverage on the website Seeking Alpha have higher bid-ask spreads and price impact. My paper complements these findings, as I show that information asymmetry and liquidity are also negatively related in the setting of alternative data. My findings are also consistent with studies regarding the rise in information asymmetry due to an exogenous reduction in sell-side analyst coverage. Kelly and Ljungqvist (2012) find that bid-ask spreads and amihud illiquidity ratios both rise after a reduction in analysts and Chen et al. (2018) show that hedge funds trade and profit more after this decreased analyst coverage. Looking specifically at the release of alternative data, Zhu (2018) finds an increase in stock price efficiency, suggesting a decrease in asymmetric information between firm insiders and investors. Rather than studying the relation between insiders and investors, my paper focuses on the information environment between different subgroups of investors, finding that asymmetric information rises in this setting and leads to lower liquidity.

2.2 Data

2.2.1 Satellite Image Data

I obtain data on parking lot car counts from Orbital Insight, an image processing company that uses machine learning to convert satellite images into quantitative data. My sample period begins in January 2010 and ends in December 2017.[8] Orbital Insight uses a representative sample of each firm's parking lots to construct a variable for the average number of cars at a firm's retail stores on a given day. Their normalization process accounts for variation in traffic at different times of day as well as factors unique to certain stores. For example, the normalization process considers whether a Wal-Mart is a standard location or a larger Super Wal-Mart location. Notably, data on traffic volume is generally available around 16 hours after an image is taken, so investors can make timely trades based on this information.

Figure 2.1 shows a sample parking lot image for a Wal-Mart store in Arizona. Orbital Insight draws a "mask" for each parking lot in order to reduce the possibility that cars parked at other stores enter the data. Each circle in the figure represents a car identified by the algorithm. Only circles within the shaded area are counted towards Wal-Mart's car count for that day.

To predict future monthly stock returns, I measure traffic growth as the difference between the log of the average car count for a month minus the log of average car count 12 months prior. This method of measuring growth reduces the possibility that noise from seasonality will affect the predictive power of the measure. Figure 2.2 shows average daily car counts for firms in my sample, emphasizing the importance of adjusting for seasonality in parking lot traffic. The average car count for all stocks is shown in panel A. The graph shows that average car counts spike during November and December as consumers prepare

[8]Note that the data from Orbital Insight starts in 2009, with the first year being used to train their model.

for the holiday season. Average car counts are lower in January and February, likely due to cold weather dissuading consumers from leaving their homes. Panels B and C show seasonal car counts for Wal-Mart and Home Depot, respectively. Wal-Mart's average car counts are similar to the average covered firms, with more cars in parking lots in December and fewer cars in January. Home Depot follows a unique pattern, as the bulk of the company's sales come in spring. As a result, Home Depot's car counts are higher than average from April to June. These differing patterns in car counts are adjusted for by using the year-over-year car count measure.

To illustrate how micro-level traffic patterns reveal novel information about stock prices, consider Figure 2.3, which compares cumulative year-over-year growth in car traffic with cumulative stock returns for Bed Bath and Beyond from 2011 to 2017. The two variables trend in similar directions, though the growth in car count variable appears to be a leading indicator of stock returns. The satellite data shows a growth in car count for Bed Bath and Beyond from the beginning of the sample and peaking at the start of 2013. The cumulative stock return follows a similar upward trend but does not peak until the end of 2013. A downward trend in car count begins in February of 2013, which is not reflected in stock prices until November of 2013. A final decline in car counts begins in April 2015, which follows closely with a decline in stock returns. This example represents a systematic pattern across US retailers: traffic patterns reveal novel information about stock prices that can be used to generate abnormal returns.

I merge the satellite data with stock return data from CRSP and firm accounting data from Compustat. I also obtain factor data for market return (MKTRF), size (SMB), value (HML), momentum (UMD), profitability (RMW), and investment (CMA) from Ken French's data library.

Table 2.1 presents summary statistics for the full sample of covered firms as separated by each release period. The average growth in car count is slightly negative at -0.5% with an interquartile range of 8.08%. Orbital Insight had two main decision criteria for choosing which firms to cover in their initial release. First, the firms had to be large U.S. firms that would therefore be covered by a larger number of investors. Second, the companies must have enough store locations to generate a reliable normalized measure of car counts. Therefore, the size and level of turnover of firms in Release 1 are larger on average than in subsequent releases. Firms in Release 1 also tend to be more value stocks, as evidenced by their lower average book-to-market. I include these characteristics as well as past stock returns in all regressions to control for differences in these characteristics between release periods.

2.2.2 Institutional Investor Holdings

To identify institutional investors, I use the 13f institutional holdings data from Thomson Reuters. Institutions with over $100 million in assets are required to fill out the quarterly 13f forms for all U.S. equity positions exceeding $200,000 or 10,000 shares. I identify hedge funds in this database following the methodology of Brunnermeier and Nagel (2004) and Griffin and Xu (2009). More specifically, hedge funds are identified by matching the 13f fund names with names from five hedge fund databases: BarclayHedge, HFR, Eureka, Lipper TASS, and Morningstar.[9] I designate all funds not matched through this process as

[9]See Cao, Chen, Goetzmann, and Liang (2016) for more detail on the hedge fund identification process.

non-hedge funds. Non-hedge funds include other institutional investors like mutual funds, insurance companies, and banks. The final sample for the 2010 to 2017 period includes 659 hedge funds and 4,427 non-hedge funds.

I define abnormal holdings for hedge funds and non-hedge funds using the following equation:

$$Abn\_HF_{i,q} = \left(\frac{Shares\ Owned^{HF}_{i,q}}{Shares\ Out_{i,q}}\right) - \frac{\sum_{t=q-4}^{t=q-1}\left(\frac{Shares\ Owned^{HF}_{i,t}}{Shares\ Out_{i,t}}\right)}{4} \tag{2.1}$$

where $Shares\ Owned_{i,q}$ is the total number of shares of stock i held by hedge funds in quarter q and $Shares\ Out_{i,q}$ is the total number of shares outstanding for stock i in quarter q. Abnormal holdings for non-hedge funds are defined analogously. Table 2.1 shows that average abnormal holdings of firms in my sample for hedge funds (non-hedge funds) is -0.07 (0.15) with an interquartile range of 3.37 (5.37).

2.2.3 Individual Investor Order Imbalances

I use the Trade and Quote (TAQ) dataset to measure individual investor activity. I follow Boehmer, Jones, and Zhang (2017), who provide a clean method to identify individual investor order flow. Boehmer et al. (2017)'s method exploits the tendency for individual investors' order flow to be internalized or sent to wholesalers. Individual orders typically receive price improvements of a fraction of a penny to compensate for this internalization or whole-selling. Therefore, individual initiated buy orders will have transaction prices slightly below the round penny and sell orders slightly above the round penny. Further, these transactions typically happen off the exchange and are therefore labeled in TAQ with exchange code "D". These institutional features allow me to identify a clean sample of individual investor initiated transactions in order to measure individual investor demand.

After collecting information on individual investor trading activity, I compute the following order imbalance measures:

$$Indiv\ OIB\ Vol_{i,t} = \frac{Ind\ Buy\ Vol_{i,t} - Ind\ Sell\ Vol_{i,t}}{Ind\ Buy\ Vol_{i,t} + Ind\ Sell\ Vol_{i,t}} \tag{2.2}$$

$$Indiv\ OIB\ Trade_{i,t} = \frac{Ind\ Buy\ Trade_{i,t} - Ind\ Sell\ Trade_{i,t}}{Ind\ Buy\ Trade_{i,t} + Ind\ Sell\ Trade_{i,t}} \tag{2.3}$$

where $Ind\ Buy\ Vol_{i,t}$ is the average buy volume by individual investors in stock i during time t and $Ind\ Sell\ Vol_{i,t}$ is the average sell volume in stock i during time t. Similarly, $Ind\ Buy\ Trade_{i,t}$ is the average number of buy trades by individual investors in stock i during time t and $Ind\ Sell\ Trade_{i,t}$ is the average number of sell trades in stock i during time t. The average $Ind\ Buy\ Vol$ in my sample is -1.9% with an interquartile range of 16.8% and the average $Ind\ Buy\ Trade$ is -1.9% with an interquartile range of 15.3%.

2.3 The Investment Value of Satellite Imagery

2.3.1 Stock Returns

In order to test whether growth in traffic to firms' stores predicts stock returns, I form portfolios based on the growth in car count measure described in section 2.2.1. At the beginning of each month, I sort stocks into quintile portfolios based on traffic growth and then track their performance over the following month. Quintile 5 contains firms with the highest growth in car count, while quintile 1 contains those with the lowest growth. I then form a high-minus-low (H-L) portfolio which goes long the stocks in quintile 5 and shorts those in quintile 1.

The performance results of the quintile portfolio sorts are reported in Table 2.2. I analyze returns using raw excess returns as well as CAPM, four-, and six-factor alphas for each portfolio. The four-factor alpha contains the excess market return (MKTRF) as well as the size (SMB), value (HML), and momentum (UMD) factors of Fama and French (1993) and Carhart (1997). The six-factor model adds the profitability (RMW) and investment (CMA) factors of Fama and French (2015). I present equal-weighted returns in Panel A and value-weighted returns in Panel B.

The results in Table 2.2 show that trading based on signals generated from alternative data can lead to significant outperformance. Across all return specifications, portfolio returns increase monotonically with the prior month's growth in car count. Focusing on excess returns, the highest quintile of stocks earns 1.86% per month while the lowest quintile earns 0.26% resulting in a long-short portfolio of 1.6%. Alphas generated from the CAPM, four-, and six-factor models suggest that factor exposures cannot explain the statistical and economic significance of the long-short portfolio. The H-L portfolios for equal-weighted returns are significant at the 1% level for all factor models and have alphas that range between 1.58% and 1.65% per month. For value-weighted returns, the H-L portfolios earn monthly alphas between 1.56% and 1.67% and are statistically significant at the 1% level.[10]

2.3.2 Return Predictability Post-Dissemination

In this section, I test the persistence of portfolio returns after the satellite data becomes available to the market. The economically large monthly alpha generated by this trading strategy creates a strong incentive for investors to seek out alternative datasets in order to capture excess profits. If enough investors begin trading on this information then the alpha generated by this strategy will eventually be arbitraged away. However, there are several arguments for why the excess profits from this strategy will persist after the data becomes available. First, the cost of alternative datasets will prohibit smaller investors from accessing them. Second, many larger discretionary funds who can afford alternative datasets do not have the right infrastructure to incorporate the data into their discretionary trading strategies.[11] Finally, the investors who have the resources to purchase and develop trading strategies from alternative data may identify different signals from the same dataset. Therefore, it is possible that the alphas generated from the trading strategy developed in this paper are not immediately arbitraged away.

[10]In the appendix I confirm that growth in car count also predicts firm fundamentals. Specifically, I find an interquartile increase in growth in car count is associated with a 14.47% increase in revenue surprise and a 0.17% increase in price-scaled unexpected earnings. Further, I confirm a substantial portion of the return realization from satellite data stems from earnings announcements, as an interquartile increase in growth in car count is associated with a 71 basis point increase in cumulative abnormal announcement returns.

[11]"Revenge of the Humans: How Discretionary Managers Can Crush Systematics" Leigh Drogen, CEO of Estimize. May 8, 2017.

To test between these two possibilities, I examine the persistence of portfolio returns using a difference-in-differences framework. Specifically, I run the following regression:

$$\begin{aligned} Excess\ Return_{i,t+1} &= \alpha + \beta_1 * Growth\ in\ Car\ Count_{i,t} + \beta_2 * Release \\ &+ \beta_3 * (Growth\ in\ Car\ Count_{i,t} \times Release) + \beta_4 * Firm\ Controls_{i,t} \\ &+ \beta_5 * Firm\ FE + \beta_6 * Year\ Month\ FE + \epsilon_{i,t} \end{aligned} \tag{2.4}$$

where $Excess\ Return_{i,t+1}$ is the stock return in month $t+1$ for stock i in excess of the risk-free rate, $Growth\ in\ Car\ Count_{i,t}$ is the growth in traffic for firm i in month t, and $Release$ is an indicator variable equal to zero for a firm in months prior to Orbital Insight releasing the data, and equal to one in the months after Orbital Insight begins selling the data. Therefore, $Growth\ in\ Car\ Count_{i,t} \times Release$ captures the marginal change in return predictability of $Growth\ in\ Car\ Count_{i,t}$ for a firm whose data has been disseminated relative to before the data is released. A negative coefficient on the interaction term would indicate that investors trade away the profitability of the trading strategy once the data becomes available.

$Firm\ Controls_{i,t}$ is a set of firm characteristics for firm i in month t. I use the following firm characteristics as controls: the log market value of equity at the end of the prior month, the log of book-to-market at the end of the prior month, the stock return from month $t-12$ to $t-2$, the log of growth in shares outstanding from month $t-36$ to month $t-1$, the change in net working capital minus depreciation in the prior fiscal year, the return on assets in the prior fiscal year, and the log of growth in total assets in the prior fiscal year. Lewellen (2015) shows that these seven characteristics have significant predictive power for stock returns. I include firm and year-month fixed effects and cluster standard errors by firm and year-month.

Table 2.3 presents the results of the difference-in-differences estimation. I first report results for return predictability for the entire sample in column 1. The coefficient on growth in car count is 0.033, significant at the 1% level. In economic terms, this means that an interquartile range increase in growth in car count is associated with a 26.6 basis point increase in the following month's excess return. This result suggests that traffic growth contains information which cannot be garnered from firm characteristics. Column 2 includes the indicator variable for whether Orbital Insight has released a firm's data as well as its interaction with growth in car count. The coefficient on the interaction term is indistinguishable from zero at standard levels of significance. This result provides evidence that the profitability of the trading strategy is not immediately traded away when the data is disseminated.

2.3.3 Limits to Arbitrage

A potential explanation for the persistence of the return predictability is arbitrage constraints. The profitability of the trading strategy may be restricted to stocks that limit arbitrageurs by being difficult to analyze or trade in large quantities. I test whether limits to arbitrage explain the persistence of return predictability of alternative data using three proxies to identify stocks more likely to have arbitrage constraints: firm size, bid-ask spread, and the amihud illiquidity ratio. For firm size, I use the market equity of the firm. I calculate bid-ask spread as the difference between the ask and bid prices divided by the average of the ask and bid prices. I follow Amihud (2002) and calculate the illiquidity measure as the average ratio of daily absolute return to dollar trading volume. I test the difference-in-difference regression from equation (2.4) on subsamples split at the median of these three proxies. If the persistent profitability of the portfolio returns are due to stocks with limits to arbitrage, then the interaction term should be significantly negative for large firms, firms with low bid-ask spreads, and firms with low amihud illiquidity ratios and insignificant for small firms, firms with high bid-ask spreads, and firms with high amihud illiquidity ratios.

Columns 3 through 8 of Table 2.3 report the results of the subsample splits. I find that, regardless of a firm's arbitrage constraints, the trading strategy based on parking lot traffic growth remains a significant predictor of future excess returns. Specifically, the coefficient on the interaction between growth in car count and release is statistically insignificant in each subsample split. These results suggest that the profitability of the alternative data trading strategy post-dissemination is not due to limits to arbitrage.

2.4 The Capital Market Consequences of Alternative Data

The investment value contained in alternative data creates an incentive for sophisticated investors to implement the data into their trading strategies. There is evidence that hedge fund managers represent the most sophisticated investors, as they often outperform mutual funds (Ackermann, McEnally, and Ravenscraft, 1999) and are able to develop informed trading strategies based on novel information (Huang, 2017). In this section I investigate how sophisticated investors adapt to the introduction of alternative data by examining the trading behavior of hedge funds around the dissemination of Orbital Insight's satellite data. Additionally, I study the trading behavior of non-hedge fund institutions and individual investors. Though non-hedge funds are likely able to afford the expense of alternative data, they are less likely to be able to turn that data into a profitable trading strategy. Individual investors lack the resources to purchase or develop trading strategies from alternative data. Further, individuals investors' tendency to be contrarian traders (Grinblatt and Keloharju (2000); Kaniel et al. (2007)) means they are likely the liquidity suppliers for the demand created by alternative data. Therefore, I expect a positive relationship between the Orbital Insight trading signal and hedge fund trading, no significant relationship between the trading signal and non-hedge fund institution trading, and a negative relationship between the trading signal and individual investor trading. Further, I expect hedge fund trades to become more profitable after the release of Orbital Insight's data, non-hedge fund trades to have no change in profitability, and individual investor trades to become less profitable.

2.4.1 Institutional Investor Holdings

To test how institutional investor trading behavior changes after the release of alternative data, I run difference-in-differences regressions of abnormal holdings for hedge funds and non-hedge funds on growth in car count around the dissemination of the satellite data. Because institutional holdings are reported quarterly, I measure growth in car count at a quarterly frequency as well. Specifically, in each quarter I examine the change in abnormal holdings for hedge funds and non-hedge funds using the following regression model:

$$\begin{aligned} Abnormal\ Holdings_{i,t} &= \beta_1 * Growth\ in\ Car\ Count_{i,t} + \beta_2 * Release \\ &+ \beta_3 * (Growth\ in\ Car\ Count_{i,t} \times Release) + \beta_4 * Firm\ Controls_{i,t} \\ &+ \beta_5 * Firm\ FE + \beta_6 * Year\ Quarter\ FE + \epsilon_{i,t} \end{aligned} \tag{2.5}$$

where $Abnormal\ Holdings_{i,t}$ is the level of abnormal holdings for either hedge funds or non-hedge funds in stock i for quarter t. I test the relationship between abnormal holdings and growth in car count in contemporaneous quarters as clients of Orbital Insight are able to access the data with only a 16-hour lag. Therefore, the coefficient on ($Growth\ in\ Car\ Count_{i,t} \times Release$) estimates the sensitivity of fund's holdings to the growth in car count measure in the post-dissemination period relative to the pre-dissemination period. I include stock-level controls for prior quarter returns adjusted for the returns of the CRSP value-weighted index, book-to-market, size, and turnover. I cluster standard errors by firm and year-quarter.

Table 2.4 presents the regression results. The coefficient on growth in car count is insignificant in all specifications for both hedge funds and non-hedge funds, implying that neither type of institutional investor was able to trade based on parking lot growth prior to the availability of the satellite data. However, the coefficient on the interaction term is significantly positive for abnormal hedge fund holdings and insignificant for non-hedge fund holdings. Specifically, the regression using year-quarter fixed effects (column 1) shows that an interquartile increase in quarterly growth in car count (8.7%) leads to a 50 (8.7*0.057) basis point increase in abnormal hedge fund holdings in firms whose satellite data has been released relative to firms whose data has not been released. A 50 basis point increase in abnormal hedge fund holdings represents 14.2% percent of the interquartile range (3.37%). Looking within-firm, column 2 shows that an interquartile increase in car count growth is associated with a 70.47 basis point increase in abnormal hedge fund holdings for a firm in the post-dissemination period relative to the pre-dissemination period. The coefficient on the interaction term remains positive and significant when both year-quarter and firm fixed effects are included.

The results when looking at non-hedge funds show no effect of satellite data availability on abnormal holdings. The specification including year-quarter and firm fixed effects for abnormal non-hedge fund holdings leads to an insignificant coefficient on the interaction term of -0.014. These findings are consistent with the expectation that sophisticated investors take advantage of the availability of alternative data.

2.4.2 Institutional Investor Profitability

I next test whether institutional holdings become more profitable after alternative data is available. I hypothesize that hedge funds' better information processing abilities allow them to profit more on trades in stocks that have alternative data available. I estimate the following regression model to examine how abnormal holdings for hedge funds and non-hedge funds perform around the release of Orbital Insight's data:

$$\begin{aligned} Adjusted\ Stock\ Returns_{i,t+1} = {} & \beta_1 * Abnormal\ Holdings_{i,t} + \beta_2 * Release \\ & + \beta_3 * (Abnormal\ Holdings_{i,t} \times Release) + \beta_4 * Firm\ Controls_{i,t} \\ & + \beta_5 * Firm\ FE + \beta_6 * Year\ Quarter\ FE + \epsilon_{i,t} \end{aligned} \tag{2.6}$$

where all variables are defined the same as in previous regressions. I expect a significantly positive coefficient on ($Abnormal\ Holdings_{i,t} \times Release$) for hedge funds and a coefficient near zero for non-hedge funds.

Results for regressions using equation (2.6) are reported in Table 2.5. As expected, abnormal hedge fund holdings become more predictive of future returns once there is alternative data coverage on a stock. In terms of economic magnitude, the regression in column 1 shows that an interquartile increase in abnormal hedge fund holdings is associated with 1.35% (3.734*0.004) increase in the next quarter's adjusted stock returns in stocks whose data has been released relative to unreleased stocks. This 1.35% increase represents 6.36% of the interquartile range for adjusted stock returns. The results when using firm fixed effects show an interquartile increase in abnormal hedge fund holding leads to a 2.02% (3.374*0.006) increase in returns for a stock after its data has been made available relative to the pre-dissemination period. The coefficient on the interaction term remains significant when both time and firm fixed effects are included. Columns 4 through 6 show abnormal non-hedge fund holdings have no change in stock return predictability around the release of the satellite data, as the coefficient on the interaction term is insignificant in all specifications. Collectively, the results in Tables 2.4 and 2.5 suggest that hedge funds are better able to take advantage of big data compared to other institutional investors.

2.4.3 Individual Investor Trading

Given the large expense to access big data, individual investors are not the target client for alternative data providers. Because individual investors are on average contrarian traders (Grinblatt and Keloharju (2000); Kaniel et al. (2007)), it is possible that individuals provide liquidity to meet sophisticated investor demand for stocks with alternative data coverage. Although contrarian trading has historically led to positive excess returns for individual investors (Kaniel et al. (2007)), the asymmetric information environment brought on by alternative data could lead to negative returns on trades made by individual investors. In this section, I test this idea by examining how the sensitivity of individual order demand in relation to growth in car count changes around the release of alternative data. Specifically, I run the following regression:

$$\begin{aligned} Individual\ OIB_{i,t} &= \beta_1 * Growth\ in\ Car\ Count_{i,t} + \beta_2 * Release \\ &+ \beta_3 * (Growth\ in\ Car\ Count_{i,t} \times Release) + \beta_4 * Firm\ Controls_{i,t} \\ &+ \beta_5 * Firm\ FE + \beta_6 * Year\ Month\ FE + \epsilon_{i,t} \end{aligned} \tag{2.7}$$

where $Individual\ OIB_{i,t}$ refers to either the volume or trade order imbalance for individual investors in stock i in month t. The coefficient on $(Growth\ in\ Car\ Count_{i,t} \times Release)$ measures how individual investor demand for a stock relative to a firm's traffic growth changes when alternative data is released.

The first three columns of Table 2.6 provide results of estimating equation (2.7) for the order imbalance of individual investor trade volume. Interestingly, the coefficient on growth in car count is significantly positive (thought economically small with a magnitude of 0.0004), suggesting that individual investors are able to trade in the same direction as traffic growth before alternative data is available. This result is consistent with the literature that finds individual investors are informed (Kaniel, Liu, Saar, and Titman (2012); Kelley and Tetlock (2013); Boehmer et al. (2017)). However, individual order flow becomes significantly less sensitive to traffic growth once access to the satellite data becomes available. Looking at column 3, a 1% increase in growth in car count is associated with 6.4% decrease in individual volume order demand in the post-dissemination period relative to the pre-dissemination period. Similar results are found when looking at the order imbalance for the number of individual trades in columns 4 through 6.

2.4.4 Indiviudal Investor Profitability

I next investigate the profitability of individual investor demand for stocks whose parking lot data is sold by Orbital Insight. Due to the granular nature of TAQ data, I am able to examine how investor demand immediately prior to earning announcements is able to predict announcement returns. The decrease in individual investor demand to traffic growth shown in Table 2.6 suggests that individual demand will become less informed after alternative data becomes available. I use the following model to examine whether there is a change in individual investor profitability:

$$\begin{aligned} Cumulative\ Abnormal\ Returns_{i,t,d\ to\ d+3} &= \beta_1 * Individual\ OIB_{i,t,d-3\ to\ d-1} + \beta_2 * Release \\ &+ \beta_3 * (Individual\ OIB_{i,t,d-3\ to\ d-1} \times Release) + \beta_4 * Firm\ Controls_{i,t} \\ &+ \beta_5 * Firm\ FE + \beta_6 * Year\ Quarter\ FE + \epsilon_{i,t} \end{aligned} \tag{2.8}$$

where $Cumulative\ Abnormal\ Returns_{i,t,d\ to\ d+3}$ is the abnormal announcement return for stock $i's$ earnings announcement for quarter t from the day of the announcement until three days after and $Individual\ OIB_{i,t,d-3\ to\ d-1}$ is the individual order imbalance for either volume or trades for stock i for the three days prior to the earnings announcement for quarter t. The interaction term will therefore measure how the profitability of individual investor demand changes after the introduction of alternative data to the market.

Table 2.7 reports the regression results. Consistent with expectations, individual investor demand becomes significantly worse at predicting announcements returns after satellite data for a company becomes available. Looking at column 3, a 1% increase in three day individual order imbalance is associated with a 4.7 basis point decrease in cumulative abnormal announcement returns in the post-dissemination period relative to the pre-dissemination period. This result holds for all specifications shown and for order imbalance measures using both volume of shares and number of shares traded.[12] Together, Tables 2.6 and 2.7 provide supporting evidence for the notion that individual investors become relatively less informed when alternative data is introduced.

2.4.5 Liquidity Implications for Affected Firms

The introduction of alternative data to the market represents a change in the informational environment between market participants. As large sophisticated investors are the only group that can feasibly make use of alternative data, these investors gain an informational advantage over other investors in the market. Theoretical research generally concludes that an increase in information asymmetry between market participants leads to an increase in stock illiquidity.[13] Therefore, it is possible that the release of satellite data by Orbital Insight leads to a decrease in the liquidity of affected firms' stocks.

Table 2.8 reports evidence consistent with this conjecture. The table reports regression results of stock liquidity measures on an indicator variable equal to one if a firm's satellite data has become available to investors. I use the bid-ask spread and the amihud illiquidity ratio as measures of stock liquidity. Looking at columns 2 and 5, which analyze within-firm changes in liquidity by including firm-level fixed effects, I find a significant increase in both liquidity measures. Specifically, the release of Orbital Insight's satellite data is associated with an increase in the amihud illiquidity ratio of 0.003 which represent a 30.00% increase

[12] Results are also robust to using order imbalance measures for a one day or five day period prior to the earning announcement date.

[13] Some examples of theoretical papers in this line of research include Copeland and Galai (1983), Glosten and Milgrom (1985), Kyle (1985), and Easley and O'hara (1987).

from the mean amihud of 0.01. Similarly, the bid-ask ratio increases by 0.04, representing a 30.08% increase from the mean.

I account for omitted factors that could introduce a time trend by including year-month fixed effects in columns 3 and 6. Release is identified in this setting due to the staggered introduction of the satellite data by Orbital Insight. Though the magnitudes on the coefficients are reduced, I continue to find positive coefficients on the release indicator variable for both liquidity measures. Under this specification, the amihud illiquidity ratio for firms whose data has been disseminated is 20% higher than the average firm. Likewise, the bid-ask spread is 3.8% higher (though the coefficient is insignificant at conventional levels). These results are consistent with the literature that finds that stock liquidity decreases in environments with increasing informational symmetry.

2.5 Conclusion

I contribute to the understanding of alternative data's impact on financial markets by documenting the investment value of a leading satellite imagery provider's data and examining how the dissemination of this data affects investor trading behavior. Using a measure of the growth in the number of cars in US retail firms' parking lots, I show that a long-short trading strategy based on alternative data earns monthly alphas of 1.6%. These abnormal returns persist even after the data is made available to market participants.

Using the staggered introduction of the satellite data as a natural experiment, I find market participants react to the dissemination of this data. In particular, hedge funds begin to trade in the direction of the growth in car count measure after the data is released, while individual investor demand trends the opposite way. Further, hedge fund trades become more profitable and individual investor demand becomes less profitable. Finally, the increase in information asymmetry between market participants leads to lower liquidity for covered firms' stocks.

Alternative data has become an essential resource for investors looking for an informational advantage. This type of data will continue to impact financial markets as more datasets are introduced. Collectively, my findings illustrate the power of alternative data both in its ability to generate value and in its influence on the functioning of capital markets.

Table 2.1: Summary Statistics

This table reports descriptive statistics for firms with satellite data from January 2010 through December 2017. Growth in car count is the natural log of car count minus the natural log of car count from 12 months prior. Car count is the monthly average of cars observed each day in a firm's parking lots. Excess return is the monthly stock return in excess of the risk free rate. Abn_HF is the current quarter aggregate hedge fund holdings for a stock minus the average aggregate hedge fund holdings over the prior four quarters. Abn_nonHF is calculated analogously for all non-hedge fund institutions. Indiv OIB Vol is the monthly volume of trades initiated as buys by individual investors minus the volume of trades initiated as sells by individual investors divided by the sum of both buy and sell individual-initiated orders. Indiv OIB Trade is calculated analogously for the number of individual trades. Bid-Ask is the monthly average of the daily ask price of a stock minus the bid price of a stock divided by the average of the ask and bid price. Amihud is the absolute return of a stock divided by that stock's dollar volume and multiplied by 1000000. ln(Size) is the log of the market capitalization of the firm, calculated as the share price multiplied by the number of shares outstanding. ln(B/M) is the log book value of equity minus the log market value of equity. ln(Turnover) is the log of the number of shares traded by shares outstanding over the prior 12 months. Return data comes from CRSP, accounting data from Compustat, institutional investor data from 13f filings, individual investor data from TAQ, and satellite data from Orbital Insight.

	Mean	Std Dev	25th	Median	75th
Growth in Car Count	-0.495	7.201	-4.580	-0.702	3.495
Excess Return	0.642	18.425	-10.774	-0.508	10.939
Abn_HF	-0.067	3.538	-1.776	-0.063	1.598
Abn_nonHF	0.152	5.921	-2.417	0.097	2.951
Indiv OIB Vol	-0.019	0.167	-0.100	-0.009	0.068
Indiv OIB Trade	-0.019	0.146	-0.091	-0.01	0.062
Bid-Ask	0.133	0.213	0.028	0.053	0.119
Amihud	0.010	0.0280	0.0001	0.0006	0.004

	Full Sample		Release=1		Release=2		Release=3		Beta-Mode	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
ln(Size)	7.559	1.70	8.373	1.82	6.846	1.24	7.382	1.69	7.059	1.29
ln(B/M)	-0.898	0.89	-0.990	0.77	-0.852	1.14	-0.851	0.76	-0.810	0.79
ln(Turnover)	-1.553	0.72	-1.375	0.58	-1.686	0.73	-1.530	0.88	-1.787	0.69

Table 2.2: Growth in Car Count Portfolio Sorts - Quintiles

This table reports abnormal return estimates for a trading strategy that sorts stocks into quintiles based on car counts from satellite parking lot data. Stocks are sorted at the beginning of every calendar month based on the growth in car count in the prior month. In Panel A (B) stocks are equal (value) weighted within a given portfolio. Portfolios are rebalanced monthly. The "H-L" portfolio represents the difference in returns between stocks with the highest growth in car count (Q5) and stocks with the lowest car count (Q1). Abnormal returns are reported as the return in excess of the market, CAPM alpha, four-factor alpha, and six-factor alpha. The four-factor model includes factors for the excess market return (MKTRF) as well as size (SMB), value (HML), and momentum (UMD) factors of Fama and French (1993) and Carhart (1997). The six-factor model adds the profitability (RMW) and investment (CMA) factors of Fama and French (2015). t-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Panel A: Equal Weights	Q1(Low)	Q2	Q3	Q4	Q5(High)	**H-L**
Excess Returns	0.26	0.69	0.98*	1.07**	1.86***	**1.60*****
	(0.46)	(1.27)	(1.76)	(2.06)	(3.13)	**(5.57)**
CAPM Alpha	-1.03***	-0.55	-0.24	-0.13	0.54	**1.58*****
	(-2.77)	(-1.40)	(-0.60)	(-0.37)	(1.31)	**(5.49)**
Four-Factor Alpha	-0.96***	-0.50	-0.16	-0.08	0.69*	**1.65*****
	(-2.67)	(-1.28)	(-0.42)	(-0.26)	(1.94)	**(5.70)**
Six-Factor Alpha	-1.15***	-0.72**	-0.41	-0.30	0.45	**1.60*****
	(-3.38)	(-2.04)	(-1.20)	(1.09)	(1.47)	**(5.41)**

Panel B: Value Weights	Q1(Low)	Q2	Q3	Q4	Q5(High)	**H-L**
Excess Returns	0.74	0.97**	1.23***	1.59***	2.41***	**1.67*****
	(1.41)	(2.05)	(3.00)	(3.61)	(4.79)	**(4.43)**
CAPM Alpha	-0.38	-0.03	0.32	0.71*	1.27***	**1.65*****
	(-0.98)	(-0.09)	(0.97)	(1.93)	(3.68)	**(4.19)**
Four-Factor Alpha	-0.47	-0.11	0.17	0.59*	1.15***	**1.62*****
	(-1.20)	(-0.29)	(0.55)	(1.71)	(3.41)	**(4.41)**
Six-Factor Alpha	-0.57	-0.3	-0.03	0.42	0.99***	**1.56*****
	(-1.46)	(-0.91)	(-0.10)	(1.35)	(3.07)	**(4.24)**

Table 2.3: Alternative Data Return Predictability Post-Dissemination

This table reports regressions of the following form:

$$Excess\ Return_{i,t+1} = \alpha + \beta_1 * Growth\ in\ Car\ Count_{i,t} + \beta_2 * Release + \beta_3 * (Growth\ in\ Car\ Count_{i,t} \times Release) + \beta_4 * Cont_{i,t} + \epsilon_{i,t}.$$

$Excess\ Return_{i,t+1}$ is the return on stock i in month t in excess of the risk-free rate. $Growth\ in\ Car\ Count_{i,t}$ is the natural log of car count for firm i in month t minus the natural log of car count from 12 months prior. *Release* is an indicator variable equal to one in months when a stock's satellite data is available to market participants and zero otherwise. $Cont_{i,t}$ is a vector of the following controls: the log market value of equity at the end of the prior month, the log of book-to-market at the end of the prior month, the stock return from month $t-12$ to $t-2$, the log of growth in shares outstanding from month $t-36$ to month $t-1$, the change in net working capital minus depreciation in the prior fiscal year, the return on assets in the prior fiscal year, and the log of growth in total assets in the prior fiscal year. Columns 3 through 8 split the sample at the median of market equity, bid-ask spread, and amihud illiquidity ratio (defined in Table 2.1). t-statistics, calculated using standard errors clustered by firm and year-month, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Dependent Variable: Excess Stock Return					
	Full Sample	Full Sample	Large Firms	Low Spread	Low Amihud	Small Firms	High Spread	High Amihud
Growth in Car Count	**0.033*** **	**0.029*** **	**0.049*** **	**0.052*** **	**0.050*** **	**0.018* **	**0.013**	**0.017* **
	(3.860)	**(3.312)**	**(4.000)**	**(4.148)**	**(3.746)**	**(1.985)**	**(1.364)**	**(1.913)**
Growth in Car Count × Release		**0.028**	**0.012**	**0.002**	**0.018**	**0.026**	**0.042**	**0.023**
		(0.870)	**(0.221)**	**(0.037)**	**(0.317)**	**(0.698)**	**(1.095)**	**(0.608)**
Release		0.035	1.136**	0.368	0.785	-1.555	-0.333	-1.586
		(0.067)	(2.152)	(0.753)	(1.583)	(-1.350)	(-0.269)	(-1.353)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YM FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,679	10,679	5,388	5,458	5,534	5,290	5,162	5,086
R-squared	0.195	0.195	0.259	0.265	0.250	0.199	0.202	0.203

Table 2.4: Growth in Car Count and Institutional Holdings

This table reports difference-in-differences regressions of the following form:

$$Abnormal\ Holdings_{i,t} = \beta_1 * Growth\ in\ Car\ Count_{i,t} + \beta_2 * Release + \ \beta_3 * (Growth\ in\ Car\ Count_{i,t} \times Release) + \beta_4 * Cont_{i,t} + \epsilon_{i,t}$$

$Abnormal\ Holdings_{i,t}$ is the level of abnormal holdings for either hedge funds or non-hedge funds in stock i for quarter t. $Cont_{i,t}$ is a vector of the following controls: prior quarter returns adjusted for the returns of the CRSP value-weighted index, book-to-market, size, and turnover. All other variables are defined in previous tables. t-statistics, calculated using standard errors clustered by firm and year-quarter, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Abnormal HF Holdings			Abnormal non-HF Holdings		
Growth in Car Count	-0.003	-0.008	-0.003	-0.017	0.003	-0.008
	(-0.351)	(-1.036)	(-0.305)	(-0.702)	(0.145)	(-0.324)
Growth in Car Count $\times$ Release	**0.057****	**0.081****	**0.059***	**0.006**	**-0.005**	**-0.014**
	(2.037)	**(2.423)**	**(1.882)**	**(0.074)**	**(-0.066)**	**(-0.192)**
Release	0.505	0.185	0.285	-0.422	-0.662	-0.215
	(1.682)	(0.682)	(0.820)	(-0.702)	(-1.252)	(-0.293)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes
YQ FE	Yes	No	Yes	Yes	No	Yes
Observations	3,327	3,327	3,327	3,327	3,327	3,327
R-squared	0.028	0.108	0.124	0.026	0.132	0.147

Table 2.5: The Effect of Alternative Data on Institutional Investor Profitability

This table reports difference-in-differences regressions of the following form:

$$Adjusted\ Stock\ Returns_{i,t+1} = \beta_1 * Abnormal\ Holdings_{i,t} + \beta_2 * Release + \beta_3 * (Abnormal\ Holdings_{i,t} \times Release) + \beta_4 * Cont_{i,t} + \epsilon_{i,t}$$

$Cont_{i,t}$ is a vector of the following controls: prior quarter returns adjusted for the returns of the CRSP value-weighted index, book-to-market, size, and turnover. All other variables are defined in previous tables. t-statistics, calculated using standard errors clustered by firm and year-quarter, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Adjusted Stock Returns					
Abnormal HF	-0.001	-0.003**	-0.002*			
	(-1.492)	(-2.485)	(-1.812)			
Abnormal HF × Release	**0.004***	**0.006****	**0.006****			
	(1.847)	**(2.034)**	**(2.095)**			
Abnormal non-HF				-0.000	-0.000	-0.000
				(-0.747)	(-0.610)	(-0.610)
Abnormal non-HF × Release				**0.000**	**0.001**	**0.001**
				(0.086)	**(0.470)**	**(0.470)**
Release	0.008	-0.064**	0.000	0.007	0.000	0.000
	(0.577)	(-2.217)	(0.021)	(0.552)	(0.029)	(0.029)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes
YQ FE	Yes	No	Yes	Yes	No	Yes
Observations	3,279	3,279	3,279	3,279	3,279	3,279
R-squared	0.202	0.078	0.252	0.201	0.251	0.251

Table 2.6: Growth in Car Count and Individual Investor Order Demand

This table reports difference-in-differences regressions of the following form:

$$Individual\ OIB_{i,t} = \beta_1 * Growth\ in\ Car\ Count_{i,t} + \beta_2 * Release + \beta_3 * (Growth\ in\ Car\ Count_{i,t} \times Release) + \beta_4 * Cont_{i,t} + \epsilon_{i,t}$$

$Individual\ OIB_{i,t}$ refers to either the volume or trade order imbalance for individual investors in stock i in month t. $Cont_{i,t}$ is a vector of the following controls: the log market value of equity at the end of the prior month, the log of book-to-market at the end of the prior month, the stock return from month $t-12$ to $t-2$, and the log of stock turnover in the prior month. All other variables are defined in previous tables. t-statistics, calculated using standard errors clustered by firm and year-month, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Individual OIB Volume			Individual OIB Trades		
Growth in Car Count	0.0004***	0.0004**	0.0004***	0.0005***	0.0004***	0.0005***
	(2.840)	(2.609)	(2.899)	(4.366)	(3.411)	(3.739)
Growth in Car Count x Release	**-0.056***	**-0.053**	**-0.064***	**-0.073****	**-0.064***	**-0.072****
	(-1.741)	**(-1.456)**	**(-1.786)**	**(-2.195)**	**(-1.953)**	**(-2.207)**
Release	0.002	0.010**	0.003	0.003	0.003	0.001
	(0.4634)	(2.579)	(0.583)	(0.585)	(0.588)	(0.164)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes
YM FE	Yes	No	Yes	Yes	No	Yes
Observations	10,593	10,593	10,593	10,593	10,593	10,593
R-squared	0.031	0.035	0.055	0.054	0.065	0.097

Table 2.7: The Effect of Alternative Data on Individual Investor Profitability

This table reports difference-in-differences regressions of the following form:

$$CAR_{i,t,d\ to\ d+3} = \beta_1 * Individual\ OIB_{i,t,d-3\ to\ d-1} + \beta_2 * Release + \beta_3 * (Individual\ OIB_{i,t,d-3\ to\ d-1} \times Release) + \beta_4 * Cont_{i,t} + \epsilon_{i,t} \quad (2.9)$$

$CAR_{i,t,d\ to\ d+3}$ is the abnormal announcement return for stock $i's$ earnings announcement for quarter t from the day of the announcement until three days after. $Individual\ OIB_{i,t,d-3\ to\ d-1}$ is the individual order imbalance for either volume or trades for stock i for the three days prior to the earnings announcement for quarter t. $Cont_{i,t}$ is a vector of the following controls: the standardized unexpected earnings for the quarter, prior quarter returns adjusted for the returns of the CRSP value-weighted index, book-to-market, size, and turnover. All other variables are defined in previous tables. t-statistics, calculated using standard errors clustered by firm and year-quarter, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Cumulative Abnormal Returns					
Individual OIB Vol	0.007	0.004	0.002			
	(1.024)	(0.613)	(0.382)			
Individual OIB Vol x Release	**-0.053****	**-0.047***	**-0.047***			
	(-2.105)	**(-1.725)**	**(-1.662)**			
Individual OIB Trad				0.017*	0.010	0.008
				(1.793)	(1.024)	(0.807)
Individual OIB Trad x Release				**-0.112****	**-0.115***	**-0.110***
				(-2.282)	**(-1.959)**	**(-1.847)**
Release	0.009**	0.006	0.010*	0.011**	0.007*	0.012**
	(2.170)	(1.310)	(1.920)	(2.375)	(1.849)	(2.301)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes
YQ FE	Yes	No	Yes	Yes	No	Yes
Observations	3,537	3,537	3,537	3,537	3,537	3,537
R-squared	0.023	0.078	0.089	0.024	0.080	0.090

Table 2.8: The Effect of Alternative Data on Firm Liquidity

This table reports regressions of the following form:

$$Liquidity_{i,t} = \beta_1 * Release + \ \beta_2 * Cont_{i,t} + \epsilon_{i,t}$$

$Liquidity_{i,t}$ is measured using the log of the amihud illiquidity ratio and the bid-ask spread. $Cont_{i,t}$ is a vector of the following controls: the log market value of equity at the end of the prior month, the log of book-to-market at the end of the prior month, the stock return from month $t-12$ to $t-2$, and the log of stock turnover in the prior month. All other variables are defined in previous tables. t-statistics, calculated using standard errors clustered by firm and year-month, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Amihud)			Bid-ask Spread		
Release	**0.004*** **	**0.003** **	**0.002*** **	**0.047*** **	**0.040*** **	**0.005**
	(7.002)	**(2.524)**	**(2.952)**	**(11.657)**	**(4.077)**	**(1.268)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No	Yes	No
YM FE	No	No	Yes	No	No	Yes
Observations	12,628	12,628	12,628	12,628	12,628	12,628
R-squared	0.380	0.835	0.385	0.445	0.835	0.459

Figure 2.1: Sample Satellite Image

This figure shows an example of how satellite images of parking lots are converted into car counts. This example is of a Wal-Mart store in Arizona. The circles identify each car. Only cars inside the shaded region are counted towards Wal-Mart's total car count. Source: Orbital Insight.

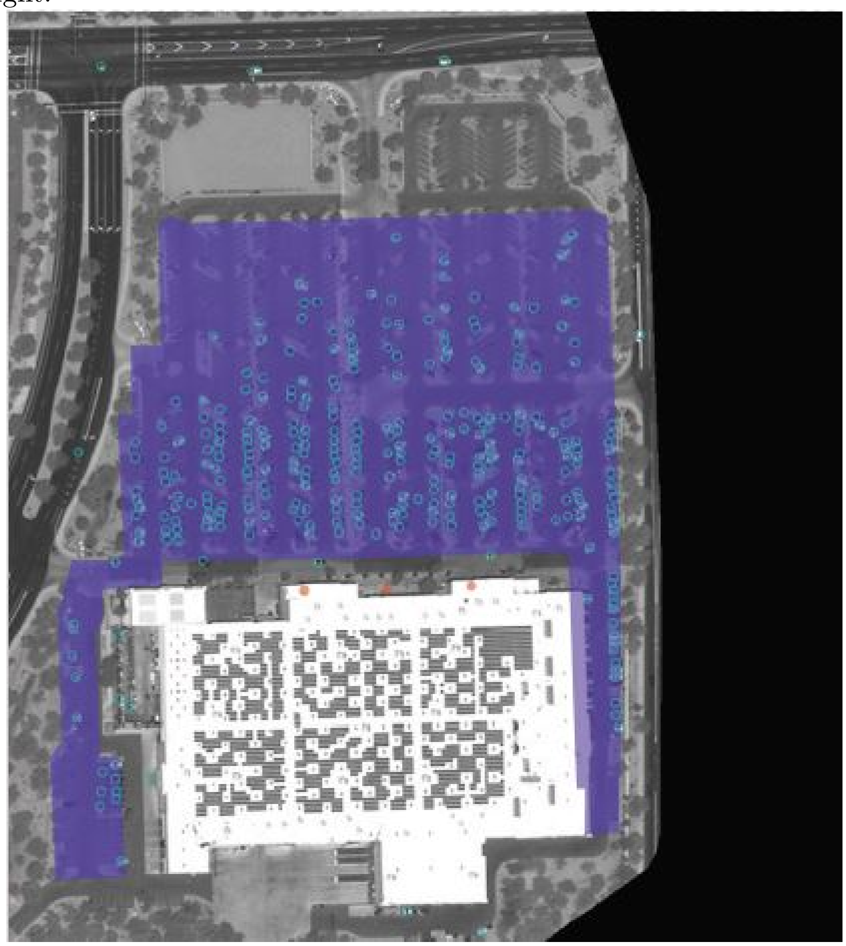
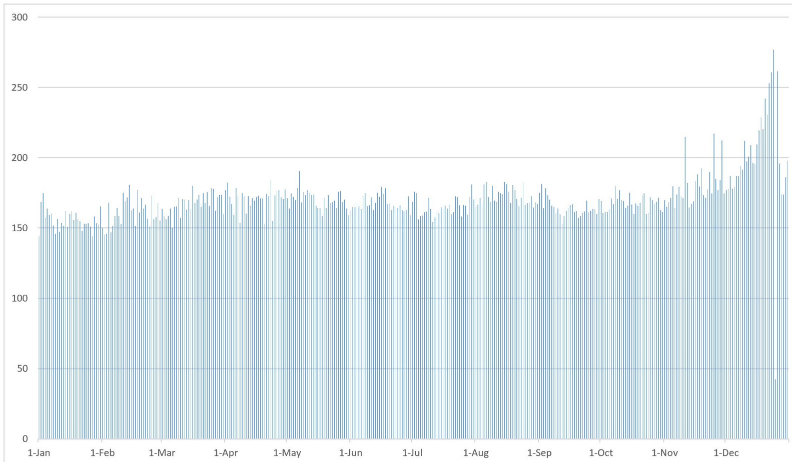


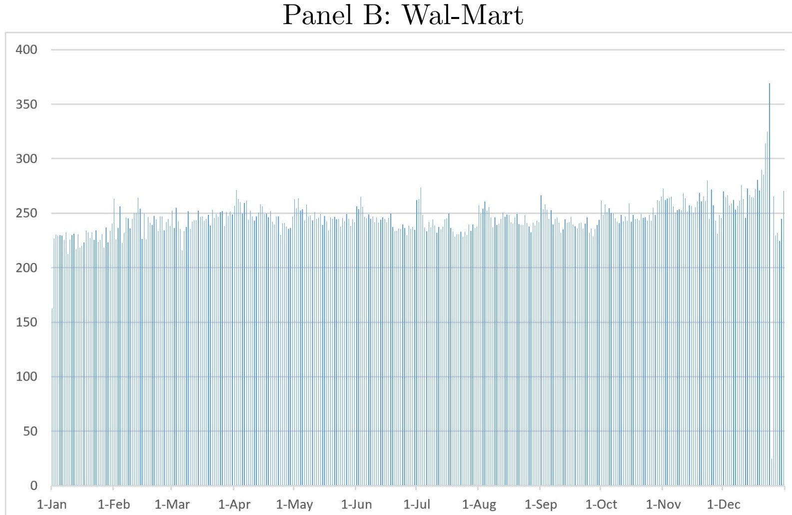
Figure 2.2: Daily Calendar Car Count

This figure shows the average parking lot car counts for each calendar day. Panel A reports averages for all stocks in the sample, Panel B reports Wal-Mart's car counts, and Panel C reports Home Depot's car counts.

Panel A: All Stocks



Panel B: Wal-Mart



Panel C: Home Depot

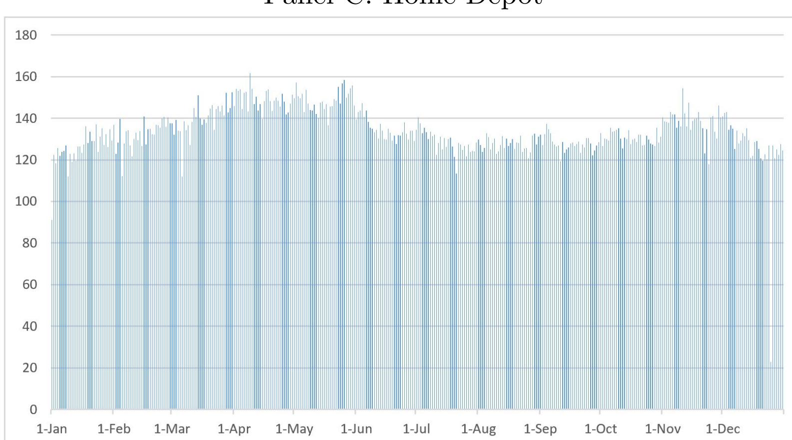
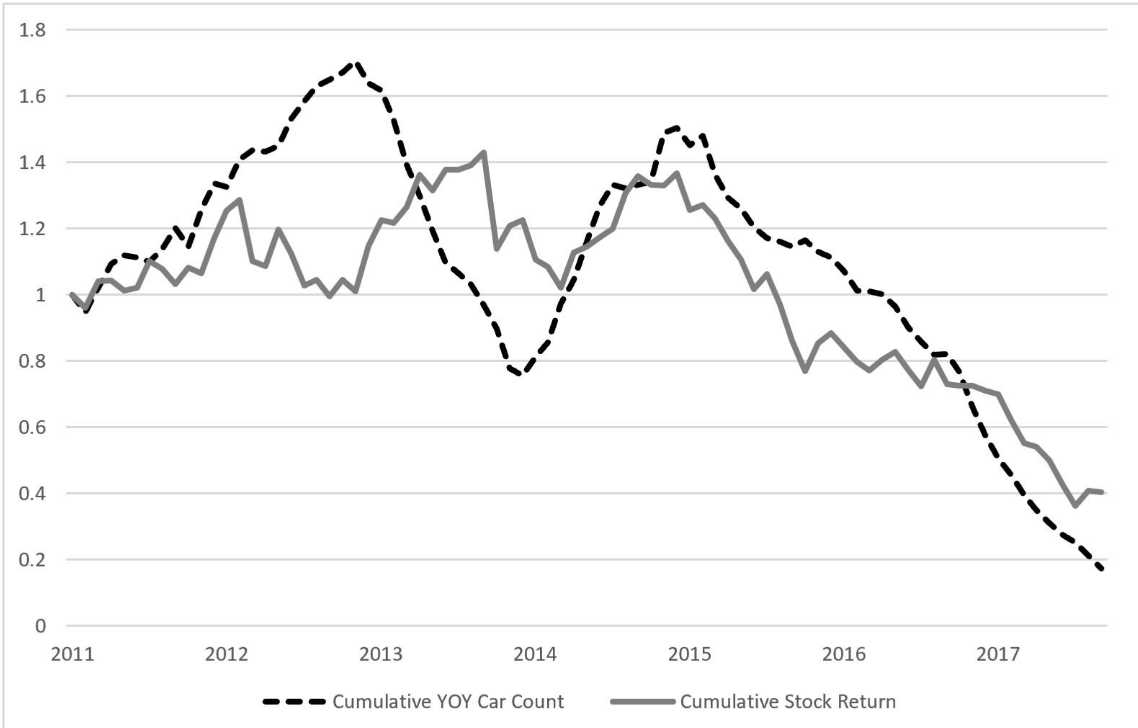


Figure 2.3: Growth in Car Count vs. Stock Return Example: Bed Bath and Beyond

This figure compares cumulative year-over-year growth in car traffic with cumulative stock returns for Bed Bath and Beyond from 2011 to 2017. Car count data is from Orbital Insight and stock return data is from CRSP.



Appendix A: Robustness checks for Chapter 1

This appendix tabulates the results of robustness checks mentioned in the dissertation.

Table A1: Maturity: robustness

This table presents robustness checks for the regressions reported in Table 5. Panel A drops all observations for bonds that were issued in Orleans Parish. Panel B also drops all observations for bonds issued in coastal counties that are not assigned a climate risk in Hallegatte et al. (2013). The dependent variable is the total annualized issuance cost of a municipal bond. t-statistics, based on errors clustered by county, are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Panel A: No New Orleans

	Long-term					Short-term				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Issue maturity:	$\geq$ 20 Years	$\geq$ 30 Years	$\geq$ 2036	$\geq$ 2041	$\geq$ 2046	$<$ 20 Years	$<$ 30 Years	$<$ 2036	$<$ 2041	$<$ 2046
Ln(Climate risk)	0.164	0.862**	0.208	0.707*	2.091**	0.011	0.064	0.058	0.077	0.078
	(1.161)	(2.583)	(1.158)	(1.646)	(2.590)	(0.085)	(0.503)	(0.457)	(0.606)	(0.613)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,155	6,659	25,281	8,484	2,092	204,421	243,832	225,273	242,019	248,381
R-squared	0.368	0.232	0.339	0.222	0.160	0.227	0.309	0.293	0.320	0.322

Panel B: No unobserved coastal

	Long-term					Short-term				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Issue maturity:	$\geq$ 20 Years	$\geq$ 30 Years	$\geq$ 2036	$\geq$ 2041	$\geq$ 2046	$<$ 20 Years	$<$ 30 Years	$<$ 2036	$<$ 2041	$<$ 2046
Ln(Climate risk)	0.110	0.849**	0.205	1.078**	3.028***	-0.055	-0.034	-0.039	-0.027	-0.031
	(0.651)	(2.230)	(0.957)	(2.289)	(2.853)	(-0.309)	(-0.192)	(-0.218)	(-0.155)	(-0.177)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,592	5,735	21,776	7,267	1,828	173,518	207,304	191,320	205,774	211,198
R-squared	0.348	0.219	0.314	0.208	0.146	0.200	0.277	0.262	0.287	0.289

Table A.2: Maturity: yield and gross spread

This table presents results for yield and gross spread separately for the regressions reported in Table 5. Panel A shows results for the long-term specifications. Panel B shows results for short-term specifications. Columns 1 through 5 report results for yield. Columns 6 through 10 report results for gross spread. t-statistics, based on errors clustered by county, are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Panel A: Long-term specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Issue maturity:	$\geq$ 20 Years	$\geq$ 30 Years	$\geq$ 2036	$\geq$ 2041	$\geq$ 2046	$\geq$ 20 Years	$\geq$ 30 Years	$\geq$ 2036	$\geq$ 2041	$\geq$ 2046
Dependent variable:	Yield	Yield	Yield	Yield	Yield	Spread	Spread	Spread	Spread	Spread
Ln(Climate risk)	0.231**	0.457	0.205*	0.288	0.663***	0.134*	0.203*	0.170*	0.178	0.217
	(2.215)	(1.632)	(1.640)	(1.316)	(2.805)	(1.785)	(1.691)	(1.878)	(1.258)	(0.799)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,248	9,108	31,107	9,998	2,458	52,623	9,430	29,285	9,954	2,599
R-squared	0.547	0.496	0.630	0.608	0.685	0.339	0.371	0.383	0.446	0.514

Panel B: Short-term specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Issue maturity:	$<$ 20 Years	$<$ 30 Years	$<$ 2036	$<$ 2041	$<$ 2046	$<$ 20 Years	$<$ 30 Years	$<$ 2036	$<$ 2041	$<$ 2046
Dependent variable:	Yield	Yield	Yield	Yield	Yield	Spread	Spread	Spread	Spread	Spread
Ln(Climate risk)	0.061	0.087	0.078	0.094	0.093	0.021	0.040	0.023	0.037	0.041
	(0.754)	(1.024)	(0.969)	(1.159)	(1.149)	(0.224)	(0.449)	(0.257)	(0.420)	(0.470)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	253,876	309,946	287,994	309,040	316,559	206,242	249,357	229,563	248,841	256,166
R-squared	0.817	0.837	0.841	0.841	0.838	0.301	0.314	0.305	0.309	0.311

Table A.3: Placebo tests: yield and gross spread

This table presents results for the regressions shown in Table 6 with yield and gross spread reported separately. Panel A shows results for various long-term specifications for the geographic matching placebo tests. Panel B shows results for various long-term specifications for the nearest neighbor matching placebo tests. The results for yield are reported in columns 1 through 6, and the results for gross spread are reported in columns 7 through 12. t-statistics, based on errors clustered by county, are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Panel A: Geographic matching

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Issue maturity:	$\geq$ 20Yr	$\geq$ 25Yr	$\geq$ 30Yr	$\geq$2036	$\geq$2041	$\geq$2046	$\geq$ 20Yr	$\geq$ 25Yr	$\geq$ 30Yr	$\geq$ 2036	$\geq$ 2041	$\geq$ 2046
Dependent var:	Yield	Yield	Yield	Yield	Yield	Yield	Spread	Spread	Spread	Spread	Spread	Spread
Ln(Climate risk)	0.021	0.115	0.281	0.118	-0.015	-0.113	-0.044	-0.059	-0.047	-0.040	0.064	0.042
	(0.188)	(0.574)	(0.843)	(0.776)	(-0.111)	(-0.278)	(-1.381)	(-1.309)	(-0.614)	(-1.354)	(0.406)	(0.488)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,248	27,355	9,108	31,107	9,998	2,458	52,623	24,514	9,430	29,285	9,954	2,599
R-squared	0.553	0.503	0.479	0.630	0.595	0.667	0.358	0.368	0.400	0.403	0.358	0.545

Panel B: Nearest neighbor matching

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Issue maturity:	$\geq$ 20Yr	$\geq$ 25Yr	$\geq$ 30Yr	$\geq$2036	$\geq$2041	$\geq$2046	$\geq$ 20Yr	$\geq$ 25Yr	$\geq$ 30Yr	$\geq$ 2036	$\geq$ 2041	$\geq$ 2046
Dependent var:	Yield	Yield	Yield	Yield	Yield	Yield	Spread	Spread	Spread	Spread	Spread	Spread
Ln(Climate risk)	-0.027	-0.048	-0.189	0.029	0.049	-0.326	-0.106	-0.191*	-0.185**	-0.181	-0.144	-0.004
	(-0.422)	(-0.476)	(-1.153)	(0.335)	(0.381)	(-1.322)	(-1.628)	(-1.768)	(-2.478)	(-1.595)	(-1.438)	(-0.036)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,248	27,355	9,108	31,107	9,998	2,458	52,623	24,514	9,430	33,246	9,954	2,599
R-squared	0.553	0.503	0.479	0.630	0.595	0.667	0.174	0.267	0.261	0.276	0.358	0.545

Table A.4: Credit rating split: robustness

This table presents robustness checks for the regressions reported in Table 7. Panel A drops all observations for bonds that were issued in Orleans Parish. Panel B also drops all observations for bonds issued in coastal counties that are not assigned a climate risk in Hallegatte et al. (2013). The dependent variable is the total annualized issuance cost of a municipal bond. t-statistics, based on errors clustered by county, are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Panel A: No New Orleans

	Long-term		Short-term	
	(1)	(2)	(3)	(4)
Credit Rating:	$<$ AA-	$\geq$ AA-	$<$ AA-	$\geq$ AA-
Ln(Climate risk)	0.738	0.136	0.140	-0.007
	(1.585)	(0.594)	(0.607)	(-0.038)
Controls	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
Observations	5,327	14,092	43,570	187,423
R-squared	0.609	0.238	0.090	0.724

Panel B: No unobserved coastal

	Long-term		Short-term	
	(1)	(2)	(3)	(4)
Credit rating:	$<$ AA-	$\geq$ AA-	$<$ AA-	$\geq$ AA-
Ln(Climate risk)	0.747*	0.189	0.352	-0.135
	(1.937)	(0.707)	(1.230)	(-0.591)
Controls	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
Observations	4,583	12,078	37,185	159,107
R-squared	0.628	0.215	0.079	0.711

Table A.5: Credit rating split: yield and gross spread

This table presents results for the regressions shown in Table 7 with yield and gross spread reported separately. Panel A reports results for the credit rating splits with yield as the dependent variable. Gross spread is the dependent variable in Panel B. *t*-statistics, based on errors clustered by county, are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Panel A: Yield

	Long-term		Short-term	
	(1)	(2)	(3)	(4)
Credit rating:	$<$ AA-	$\geq$ AA-	$<$ AA-	$\geq$ AA-
Ln(Climate risk)	0.782***	0.023	0.154	0.057
	(2.700)	(0.129)	(1.505)	(0.420)
Controls	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
Observations	7,036	20,231	50,355	241,357
R-squared	0.551	0.520	0.809	0.846

Panel B: Gross spread

	Long-term		Short-term	
	(1)	(2)	(3)	(4)
Credit rating:	$<$ AA-	$\geq$ AA-	$<$ AA-	$\geq$ AA-
Ln(Climate risk)	0.188*	0.116	-0.075	0.132
	(1.762)	(1.288)	(-1.003)	(1.183)
Controls	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
Observations	6,927	17,508	54,426	189,702
R-squared	0.461	0.349	0.365	0.306

Table A.6: Difference-in-differences of annualized issuance costs around the Stern Review: robustness

This table presents robustness checks for the regressions reported in Table 8. Panel A drops all observations for bonds that were issued in Orleans Parish. Panel B also drops all observations for bonds issued in coastal counties that are not assigned a climate risk in Hallegatte et al. (2013). t-statistics, based on errors clustered by county, are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Panel A: No New Orleans

	Long-term			Short-term		
	(1)	(2)	(3)	(4)	(5)	(6)
Time frame:	Full sample	Two years	One year	Full sample	Two years	One year
Ln(Climate risk)	-0.090	-0.202	-0.093	-0.313	-0.031	-0.064
	(-0.344)	(-1.022)	(-0.332)	(-1.000)	(-0.190)	(-0.243)
Ln(Climate risk) x Stern	0.663**	0.596*	0.285	0.360	-0.008	-0.138
	(2.081)	(1.938)	(0.814)	(1.118)	(-0.048)	(-0.487)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,546	4,998	2,404	231,045	8,577	4,142
R-squared	0.297	0.220	0.248	0.284	0.124	0.156

Panel B: No unobserved coastal

	Long-term			Short-term		
	(1)	(2)	(3)	(4)	(5)	(6)
Time frame:	Full sample	Two years	One year	Full sample	One year	Two years
Ln(Climate risk)	-0.244	-0.289	-0.267	-0.612	-0.187	-0.128
	(-0.897)	(-1.287)	(-0.997)	(-1.413)	(-0.491)	(-0.533)
Ln(Climate risk) x Stern	0.815**	0.536*	0.316	0.577	0.084	0.080
	(2.097)	(1.823)	(0.887)	(1.321)	(0.264)	(0.392)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,783	4,233	2,031	196,344	3,505	7,281
R-squared	0.276	0.229	0.260	0.252	0.156	0.127

Table A.7: Difference-in-differences of yield and gross spread around the Stern Review

This table presents results for the regressions shown in Table 8 with yield and gross spread reported separately. Yield is the dependent variable in Panel A. Gross spread is the dependent variable in Panel B. t-statistics, based on errors clustered by county, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Panel A: Yield

	Long-term			Short-term		
	(1)	(2)	(3)	(4)	(5)	(6)
Time frame:	Full sample	Two years	One year	Full sample	Two years	One year
Ln(Climate risk)	0.078	-0.222	-0.179	0.001	0.298	-0.053
	(0.630)	(-1.640)	(-1.108)	(0.003)	(0.686)	(-0.211)
Ln(Climate risk) x Stern	0.293*	0.754**	0.326	0.087	-0.189	-0.159
	(1.698)	(2.424)	(1.084)	(0.346)	(-0.536)	(-0.575)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,379	7,033	2,406	291,750	12,795	4,142
R-squared	0.512	0.168	0.266	0.835	0.107	0.155

Panel B: Gross spread

	Long-term			Short-term		
	(1)	(2)	(3)	(4)	(5)	(6)
Time frame:	Full sample	Two years	One year	Full sample	One year	Two years
Ln(Climate risk)	-0.002	-0.025	-0.152	-0.088	0.010	0.000
	(-0.019)	(-0.196)	(-1.274)	(-0.812)	(0.097)	(0.001)
Ln(Climate risk) x Stern	0.224**	0.269	0.289*	0.128	0.205	0.217
	(2.074)	(1.404)	(1.865)	(0.884)	(0.915)	(0.550)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,542	5,659	3,388	231,295	9,727	4,142
R-squared	0.348	0.231	0.282	0.313	0.294	0.295

Appendix B: Predicting Firm Fundamentals with Satellite Data

I follow the literature to develop measures for cash flow surprises. I follow Jegadeesh and Livnat (2006) and Froot, Kang, Ozik, and Sadka (2017) to construct the standardized unexpected revenue (SUR), which assumes revenue follows a seasonal random walk with a drift. Specifically, SUR for firm i in quarter q is defined using the following equation:

$$SUR_{i,q} = \frac{(Rev_{i,q} - Rev_{i,q-4}) - r_{i,q}}{\sigma_{i,q}}, \tag{10}$$

where r$_{i,q}$ and $\sigma_{i,q}$ are the average and standard deviation, respectively, of $(Rev_{i,q} - Rev_{i,q-4})$ for the prior eight quarters. The second measure I use for cash flow is standardized unexpected earnings (SUE), defined for firm i in quarter q as follows:

$$SUE_{i,q} = \frac{A(EPS_{i,q}) - F(EPS_{i,q})}{P_{i,q}}, \tag{11}$$

where $A(EPS_{i,q})$ is the actual earnings per share on the announcement date, $F(EPS_{i,q})$ is the average analyst forecasted earnings per share, and $P_{i,q}$ is the stock price at the end of the quarter. Finally, I calculate the cumulative abnormal return (CAR) for the earnings announcement as the stock return in excess over the market from one day before the earnings announcement date until three days after the announcement date. Because earnings are often reported after trading hours (Berkman and Truong, 2009), I use a five day window announcement in order to ensure that the market's complete reaction to earnings is measured. Results are robust to using a three day or four day window.

Table A.8: Firm Fundamentals and Announcement Returns

This table presents regressions of SUE, SUR, and CAR on growth in car count as well as control variables. Growth in Car Count$_Q$ is calculated as the log of average car count in the current quarter minus the log of average car count over the prior four quarters. SUR is calculated as $[(Rev_{i,t} - Rev_{i,t-4}) - r_{i,t}]/\sigma_{i,t}$ where $r_{i,t}$ and $\sigma_{i,t}$ are the average and standard deviation, respectively, of $(Rev_{i,t} - Rev_{i,t-4})$ over the prior eight quarters and $Rev_{i,t}$ is the revenue for stock i in quarter t. The control variables are the log of market equity in *t-1*, the log of book-to-market in *t-1*, the cumulative stock return from 30 days to 3 days before the earnings announcement date, and the log of turnover over the prior 12 months, and the standard deviation of analysts' EPS forecasts. t-statistics, calculated using standard errors clustered by firm and year-quarter, are reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

	(1) SUR	(2) SUE	(3) CAR
Growth in Car Count	1.793***	0.021**	0.088***
	(4.814)	(2.228)	(3.515)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
YQ FE	Yes	Yes	Yes
Observations	3,419	3,426	3,424
R-squared	0.153	0.217	0.094

References

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Zhu, Christina, 2018, Big data as a governance mechanism, *Working Paper* .

Vita

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EDUCATION

University of Missouri

B.S.B.A in Finance and Banking 2008–2012

Magna Cum Laude

EMPLOYMENT

Landmark Bank Wealth Management

Senior Portfolio Analyst 2014–2015

Portfolio Analyst 2012–2014

PUBLICATIONS

"An inconvenient cost: The effects of climate change on municipal bonds"
Journal of Financial Economics, forthcoming

- GARP Outstanding Paper in Risk Management Award at Eastern Finance Association Meeting (2018)
- Presentations: Midwest Finance Association (2018), Eastern Finance Association (2018), Financial Management Association Special PhD Paper Presentations (2018), Saint Louis University, University of Kentucky

WORKING PAPERS

"Unlevelling the playing field: The investment value and capital market consequences of alternative data

- Presentations: 9th Miami Behavioral Finance Conference Doctoral Poster Session, The Future of Financial Information Conference (Stockholm, scheduled), University of Kentucky

"Off Wall Street: How geographic diversity of analysts affects individual and consensus forecasts" (with Will Gerken)

TEACHING

University of Kentucky

Intro to Corporate Finance

Summer 2018
- Mean rating: 4.9/5 (department mean: 4.7/5)
Fall 2018
- Mean rating (2 sections): 4.4/5 (department mean: 4.1/5)
Spring 2019
- In progress

AWARDS AND GRANTS

2019	AFA Student Travel Grant
2018	GARP Outstanding Paper Award in Risk Management at Eastern Finance Association
2016	University of Kentucky FAQM Graduate Assistant of the Year
2017	Schnatter Institute Summer Grant Award
	Passed CFA Level II
2016	- CFA Institute Recognition Scholarship
2015–2019	Gatton Doctoral Fellowship
2016	Max Steckler Fellowship for Academic Achievement

PROFESSIONAL ACTIVITIES

Presentations

2019	The Future of Financial Information Conference (scheduled)
2018	Midwest Finance Association; Eastern Finance Association; FMA Doctoral Consortium & Special Ph.D. Paper Presentations; 9th Miami Behavioral Finance Conference Doctoral Poster Session; Saint Louis University; University of Kentucky

Discussant

2018	Midwest Finance Association; Eastern Finance Association