# How Does Nature Matter?*

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**Abstract**

This paper presents the first descriptive evidence on how firms spatially relate to nature through the concept of ecoregions and offers a theoretical motivation for their connection. We find empirical evidence that the performance and valuation of firms in similar ecological regions tend to comove and this effect is not fully incorporated into stock prices. A momentum strategy constructed from this lead-lag effect leads to an annualized risk-adjusted return of 11.34% (t-stat=4.11). Overall, we provide an approach that values geography when considering the relation between firms and the natural world.

**JEL Classification:** G11, G12, Q57

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It is known with reasonable confidence that species and environmental characteristics are spatially clustered (Neugarten et al., 2024; Holt et al., 2013; Humboldt and Bonpland, 1807). For example, the Andes are more diverse per acre than the Amazon basin (Rahbek et al., 2019) and many ecosystem services are only available in specific locations (Omernik and Griffith, 2014). Despite this consensus and given the perceived lack of information (Garel et al., 2024, 2025; Giglio et al., 2024), many firms and investors have been asked to understand their relationship to natural systems given the unprecedented loss in ecosystem services. The common approach to this call is to attempt to quantify dependence at the *firm-level*, given some understanding about the impacts that nature has on firms, and vice-versa[1]. In this paper, we take a different approach that is more closely aligned to the geographical literature: ecosystem services are complex, many species are unknown, and biodiversity cannot be instilled in a single number (e.g., see Fenichel and Dean, 2024; Omernik and Griffith, 2014). We simply relate the spatial distribution of firms to the spatial distribution of nature.

We provide the first descriptive evidence on how firms spatially relate to nature through the concept of ecoregions and provide empirical evidence of an *economic* connection. Ecoregions are areas where ecosystems and the types of available resources are generally similar and provide unique services. Their classification depends on factors such as geology, elevation, soils, vegetation, climate, land use, biodiversity, and hydrology, and have mostly distinct boundaries (Smith et al., 2018, 2020).

To motivate our focus on ecoregions, consider an example. The Appalachian-Blue Ridge forests in the US, a biodiversity hotspot, are characterized by moderate to high rainfall, diverse forests, the existence of grasslands and bogs, and high human interference through logging, agriculture, coal mining, and urban sprawl. The long forested ridges and valleys of the Appalachian-Blue Ridge are likely to provide many services to firms ranging from storm protection (that is, nature as insurance (Loreau et al., 2021)) to timber production, and the ecoregion has many endemic species (Edwards et al., 2013). These issues are of clear interest to companies and investors (e.g., see Dasgupta, 2021).

[1]For example, some of these measure rely on the notion of "pristine" nature, which is problematic. Humans have impacted nature for thousands of years (Omernik, 1995).

An important benefit of ecoregions is their simplicity and practicality. Unlike incomplete lists of threatened species (Bennun et al., 2018), ecoregion maps exist throughout the world and do not require site-specific information about which species have been disrupted. In fact, they provide an "appropriate scale of reference that can reflect variations in biome, habitat types, political boundaries and other natural and anthropogenic factors" (Vynne et al., 2022, p.2). They are also strongly correlated with habitat heterogeneity, a proxy of biodiversity (Tuanmu and Jetz, 2015). The use of ecoregions as a unit of analysis is also common in the scientific community. They have been shown to be a useful concept for understanding functional diversity and species assemblages (González-Maya et al., 2017), used by the World Wildlife Fund to assess global biodiversity, for conservation planning (Dinerstein et al., 2017), and to assess net primary production, carbon storage, runoff, the risk of wildfires, and habitat transformation (Yu et al., 2019)[2]. Since the change in land use is the main driver of loss of biodiversity and climate change (Lee et al., 2023; Jaureguiberry et al., 2022), it seems important for firms and investors to know where they are exposed in relation to ecoregions.

Having motivated our unit of analysis, we then extend the spatial model of Parsons et al. (2020) to incorporate ecoregions. This naturally leads us to consider whether firms in the same geographical boundary are impacted by common regional shocks (Grieser et al., 2022; Dougal et al., 2015; John et al., 2011; Coval and Moskowitz, 2001). We find that the financial performance of firms comoves within these regions, even after controlling for industry, and this effect is not appreciated by investors; leading to predictable returns. A momentum strategy built on this fact yields a six-factor risk-adjusted annualized alpha of 11.34% (t-stat=4.11).

[2]They can also be used to understand "which biomes and specific ecosystems [firm] operations interface with" and "which [operations] are located in ecologically sensitive locations" (TNFD, 2023).

# 1 Theoretical Framework

We adopt a simple model where the key aspect is that geography matters. In the model, each region $r$ offers different natural characteristics. This is a concept with a long history in the geographical literature (Smith et al., 2018; Humboldt and Bonpland, 1807). A representative firm takes factors of production $\boldsymbol{X_t^r}$ as inputs to generate output $Y_t^r$ through the function:

$$Y_t^r = F(\boldsymbol{X_t^r}, E_t^r), \tag{1}$$

where the factors of production $\boldsymbol{X_t^r}$ can be labour and physical capital, and $E_t^r$ are natural characteristics that vary by location $r$. We view $E_t^r$ as being similar to total factor productivity in that it captures some essence of comparative advantage (Dougal et al., 2015). For example, it is the production of various ecosystem services conditional on the number of functional groups (that is, species). It also captures soil fertility, precipitation, and temperature. Our task is to identify a theoretically-founded boundary for $E_t^r$. This is important if we want to understand how nature matters and how the firm relates to nature.

Demonstrating such a connection between natural characteristics and firm output, as in Eq. 1, has proven to be difficult due to the omnipresence of nature and its correlation with human factors (e.g., see Dasgupta, 2021; Henderson et al., 2018). However, there is some evidence. Giglio et al. (2023) show that if a biodiversity news index represents information about nature, then long and short positions can be taken in firms to hedge this information, consistent with an economic mechanism. The quality of nature also has a clear link to tourism (Echeverri et al., 2022) and crop production (Reilly et al., 2020). Both vary across space. The shifting attention of the forest industry to the issues of invasive species and diseases, the preservation of threatened species, and the risk of wildfires is also indicative of an economic link between firms and output (D'Amato et al., 2018).

The model takes $E_t^r$ as an important source of variation, while other factors of production $\boldsymbol{X_t^r}$ may be more homogeneous across space. This underpins our identification of how nature matters. In fact, our framework matches the approach of Giglio et al. (2024) who model output in a similar fashion to Eq. 1 at the location level, but stop short of stating what

location is or how to measure it. We agree that it is not "easy to tell compelling narratives of how dramatic loss in biodiversity over the past decades has led to large-scale declines in economic output" (Giglio et al., 2024, p.24). However, we approach the problem in terms of a conceptual and empirical challenge to measure nature.

We model the representative firm's cash flows as $Y_t - \boldsymbol{k_t}\boldsymbol{X}_t$, where $\boldsymbol{k_t}$ is a vector of flow-costs for the factors of production (Dougal et al., 2015). Firm value at $t = 0$ is:

$$P_0 = \sum_{t=1}^{T-1} E_0 \underbrace{\left[\frac{F(\boldsymbol{X_t}, E_t^r) - \boldsymbol{k_t}\boldsymbol{X_t}}{(1+\delta)^t}\right]}_{\text{expected cash flow}} + \underbrace{\frac{E_0[\pi]}{(1+\delta)^T}}_{\text{expected liquidation value}}, \tag{2}$$

where $\delta$ is the discount rate and $\pi$ is the liquidation dividend at $t = T$. Equipped with our firm value function, we then apply two geographical mechanisms to study how nature matters (Parsons et al., 2020; Tuzel and Zhang, 2017; Dougal et al., 2015; Pirinsky and Wang, 2006).

First, comovement in firm fundamentals is generated between firms that share a region $r$. Second, a lead-lag effect is generated if there is a lack of understanding about the shared connection. The intuition is that if nature offers services that vary between regions $r$, and nature is a factor of production, as our model suggests, then we can borrow approaches from the geographical literature to model this relationship.

Our geographical model follows Parsons et al. (2020). The main simplification is that we ignore other factors of production $\boldsymbol{X_t^r}$ and focus on the regional factor $r$. The result remains the same and can easily be verified by comparing it with Parsons et al. (2020, Section 2.1). Later, in our empirical approach, we introduce an industry factor to alleviate concerns that the local factor is correlated with industry, but it is not important for our exposition.

There are three dates $t = 0, 1, 2$, and two firms $i \in \{a, b\}$. In the initial period $t = 0$, the expected liquidation dividend is zero. Firms realize the liquidation dividend in $t = 2$. The liquidation dividend depends on natural characteristics $E_t^r$ and an idiosyncratic factor $\epsilon$. Because $E_t^r$ depends so strongly on location, we simply use the notation $r$. Importantly, the two firms are connected by being in the region $r_1$. The realization of firm $i$'s liquidating

dividend is then:

$$\pi_a = r_1 + \epsilon_a \tag{3}$$

$$\pi_b = r_1 + \epsilon_b, \tag{4}$$

where all factors are normally distributed, and the covariance within and between factors is zero.

At $t = 1$, firm $b$ announces important information (such as earnings). This contains valuable information for firm $a$ as it is connected to firm $b$ through its region. The question is whether this is incorporated into the valuation of firm $a$ at $t = 1$. Information other than earnings is also possible. For example, firm $b$ could be impacted by the decline in a bee population simply because they are the first to notice and inform analysts. Firm $b$ may also be at a higher latitude and therefore experience the outbreak of a disease before firm $a$ at a lower latitude. This occurred in the case of white-nose syndrome in bats, where the disease predictably followed the Ozark, Ouachita-Appalachian forests southward (Manning and Ando, 2022; Frank, 2021). The connection may also be purely cross-sectional: analysts do not, on average, think to relate firm $a$ and firm $b$ together, and only realize the connection in later periods, leading to a temporal relationship. This has been well documented (e.g., see Cohen and Frazzini, 2008) and may constitute a "hidden node" (Ammann et al., 2022).

Like Parsons et al. (2020), we let analysts $n \in \{1, 2, 3, ..., N\}$ play an important role in incorporating relevant information in $t = 1$. They are hence important for the valuation of nature. They cover stock $a$ and may also cover the region peer, firm $b$. They produce a report $\rho$ that helps investors set the price of $\pi_a$ in $t = 1$:

$$P^a_{t=1} = E[\pi_a | (\rho_1, \rho_2, \rho_3, ..., \rho_N)]. \tag{5}$$

The information available to analysts about firm $a$ is important. They could produce one of two reports in period $t = 1$ for firm $a$ (since only firm $b$ has released information): $\{\pi_b\}, \{\}$.

If analysts report $\{\}$, then $P^a_{t=1} = 0$, if $\{\pi_b\}$ is reported, $P^a_{t=1}$ equals:

$$P^a_{t=1} = \pi_b \frac{\sigma_r^2}{\sigma_r^2 + \sigma_\epsilon^2}. \tag{6}$$

The intuition is as follows. If firm $b$ is covered and the connection to firm $a$ through region $r$ is known, then analysts will incorporate the information they learn from firm $b$ into their expectations for firm $a$. In other words, they use the information in $\pi_b$ and the variance of the region shock $\sigma_r^2$. If they do not appreciate that firm $a$ and $b$ are connected by region $r$, then they simply choose $\{\}$ and the price of $a$ is 0.

We now define comovement and lead-lag effects together as the key outcomes of the model. Let the probability that $\pi_b$ is reported be $p_b(N)$. Recall the liquidating value of firm $b$, $\pi_b$, is known at $t = 1$. The mispricing of firm $a$ at $t = 1$, if any, is given by $\pi_a - P^a_{t=1}$. In other words, it is the difference between its final value $\pi_a$ and its expected value at $t = 1$. Then:

$$\begin{aligned} cov(\pi_b, \pi_a - P^a_{t=1}) &= cov(\pi_b, \pi_a) - cov(\pi_b, P^a_{t=1}) && (7)\\ &= \sigma_r^2 - cov\left(\pi_b, p_b(N)\pi_b \frac{\sigma_r^2}{\sigma_r^2 + \sigma_\epsilon^2}\right) && (8)\\ &= \sigma_r^2 - \sigma_r^2 p_b(N) && (9)\\ &= \sigma_r^2(1 - p_b(N)). && (10) \end{aligned}$$

The first term on the right-hand side of Eq. 7, $cov(\pi_b, \pi_a)$, is simply the variance of the regional factor, $\sigma_r^2$, since firm $a$ and $b$ share region $r_1$. The second term on the right hand side, $-cov(\pi_b, P^a_{t=1})$, is the covariance between the liquidating value of firm $b$, $\pi_b$, and the price of firm $a$ at $t = 1$. Since $P^a_{t=1} = \pi_b \frac{\sigma_r^2}{\sigma_r^2+\sigma_\epsilon^2}$, this simplifies to Eq. 10, the same as Parsons et al. (2020, p.4733).

Our model leads to simple propositions. The first is that firms that share a region $r$ experience a comovement in their fundamentals and valuations. We test in the context of nature by extending the work by Parsons et al. (2020) and incorporating wider geographical boundaries.

**Proposition 1.** *Firms that share a region $r$ exhibit positive cross-serial correlation in their*

*fundamentals and valuations (Eq. 1 - 4).*

The second proposition, which arrives naturally from the model but is left for future work, relates the size of the shock to each region $r$ to the degree of mispricing. A similar approach is used in Giglio et al. (2024).

**Proposition 2.** *Conditional on no incorporation of information, mispricing increases with the variance of the region shock. For example, loss of species in more fragile ecosystems leads to increased mispricing.*

The third proposition extends the approach in Parsons et al. (2020) by asking what should the appropriate geographical scale be to capture spatial effects. Since our motivation is to understand nature, we hypothesize that a geographical boundary with low variance in the type and quality of natural characteristics should better capture the services provided to firms. For example, we should not expect a clear link to the production of a firm from some arbitrary boundary that is drawn across space, and we should not expect a clear link from a boundary that contains many services since theses services are likely to counteract one another or wash away effects. In other words, the city boundaries identified in Parsons et al. (2020) and Dougal et al. (2015) are intuitive since cities have defined boundaries.

To do this, we introduce the parameter $\lambda_r \in \{0, 1\}$ that represents how well $r$ accurately captures a homogeneous set of natural characteristics. When $\lambda_r = 1$, the boundaries of $r$ capture similar natural characteristics. When it is low, $r$ is too broad or arbitrary and does not help to understand nature. We redefine the regional variance $\sigma_r^2$ to depend on the accuracy parameter $\lambda_r$. This alters Eq. 10 to become:

$$cov(\pi_b, \pi_a - P^a_{t=1}) = \lambda_r \sigma_r^2 (1 - p_b(N)). \tag{11}$$

**Proposition 3.** *As the similarity of natural characteristics in a region $r$ increases (that is, the measurement is cleaner and the variance is lower), the economic mechanism is stronger (Eq. 10 is higher).*

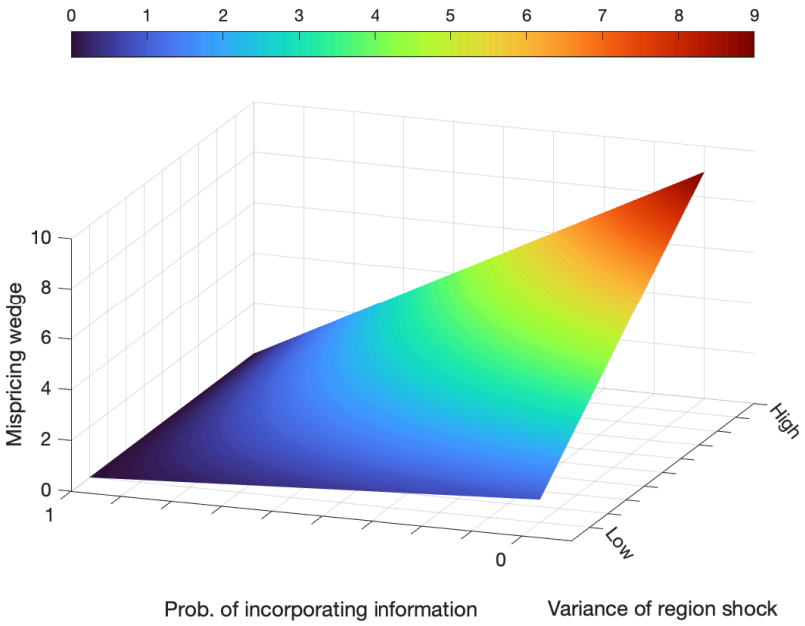
Proposition 3 stems from the fact that ecoregion maps are available at various scales. These scales capture a greater similarity of natural characteristics within regions as they

decrease in size (Omernik and Griffith, 2014, p.1253 - 1254). For example, in the United States, Level 1 ecoregions capture the clear difference between Eastern Temperature Forests, the Great Plains, and the West (mainly, North American Deserts and Northwestern Forested Mountains). However, there exist large variances *within* these regions that may have opposing effects. On the Level 2 scale, for example, the Great Plains consists of drier conditions with less agriculture in the West-Central Semi-Arid Prairies compared to the Temperate Plains.

Our focus on ecoregions $r$ consequently answers important questions; how should we capture nature? What should be the correct boundary for assessing geographical effects? Should we use metropolitan areas (Parsons et al., 2020; Tuzel and Zhang, 2017; Dougal et al., 2015; Bernile et al., 2015), states (Korniotis and Kumar, 2013), or even regions (Rosenthal and Strange, 2020)? As Rosenthal and Strange (2020) state in their review of the economics of agglomeration, there are serious confounding relationships with natural characteristics for measures of productivity such as input sharing (Tuzel and Zhang, 2017), labor market pooling, and knowledge spillovers. Perhaps even half of the variation in economic geographic concentration can be attributed to these natural characteristics (Ellison and Glaeser, 1999). In addition, natural characteristics that vary between regions, including climate, soil, and resources, have historically led to regional specialization in the United States (Holmes and Stevens, 2004). Our focus on defining $r$ is motivated by this literature.

We visualize the predictions of the model in Figure 1.

Figure 1: Predictions of the model.



# 2 Empirical Strategy

Our task is to link ecoregions to firms in a meaningful way. We first link headquarters locations to three scales of ecoregions for almost 10,000 US common stocks over 1996 - 2022. This gives us an approximate sense of the spatial distribution of firms throughout nature, with the significant caveat that we do not have a complete picture of their footprint or supply chain. This is a concern, but we are reassured by the results in Grieser et al. (2022), Carvalho et al. (2021), and Garcia and Norli (2012) that show that economic outcomes are similar when using the headquarters as the proxy for a firm's location or more granular geographical measures. Dougal et al. (2015) and Pirinsky and Wang (2006) also provide evidence that headquarters are a useful proxy for firms' economic activities.

To understand how nature matters economically, we focus on the comovement between stocks. The intuition is that local shocks and services will impact firms in a similar way if they share a common boundary. Comovement in returns or firm fundamentals is a sign that fundamentals depend on common regional factors (Tuzel and Zhang, 2017). We follow the spatial and lead-lag literature as it is well suited for this task (e.g., see Korniotis and Kumar, 2013; Hirshleifer and Shumway, 2003; Lo and MacKinlay, 1990). Certain stocks show a more immediate response to information than others. This lead-lag phenomenon is frequently attributed to the slow diffusion of information and to the varying levels of investor attention to complex economic interconnections. Recent evidence has found such lags in customer-supplier relationships (Cohen and Frazzini, 2008), industry-specific insights (Hou, 2007), and the colocation of firms within cities (Parsons et al., 2020).

To test comovement in fundamentals and returns, we borrow the approach in Parsons et al. (2020) and Pirinsky and Wang (2006):

$$X_{i,e,j,t} = \alpha + \beta_1 \underbrace{\bar{X}_{e,\notin j,t}}_{\text{ecoregion}} + \beta_2 \underbrace{\bar{X}_{\notin e,j,t}}_{\text{industry}} + \epsilon_{i,e,j,t}, \tag{12}$$

where $\bar{X}$ is mean investment ($\Delta$ total assets), sales ($\Delta$ revenue), cash flow ($\Delta$ net income), or excess returns for stock $i$ in ecoregion $e$ and industry $j$, and $t$ is the period. The ecoregion effect $\beta_1$ uses stocks in the same ecoregion $e$ but in all other industries $\notin j$. Similarly, the

industry effect $\beta_2$ uses stocks in the same industry $j$ but in all other ecoregions $\notin e$. We winsorize the fundamentals at the 1% and 99% level and require a minimum of 6 industries to exist in each ecoregion and a minimum of 6 firms to exist in each industry to control for outliers. We also consider other boundaries for the ecoregion portfolio to provide us with a benchmark: city, state, division, and region. This allows us to replicate the results in Parsons et al. (2020).

We then estimate Fama and MacBeth (1973) regressions to test the lead-lag effect. Specifically, we estimate:

$$r_{i,e,j,t+1} = \alpha + \beta_1 \underbrace{\bar{X}_{e,\notin j,t}}_{\text{ecoregion}} + \beta_2 \underbrace{\bar{X}_{\notin e,j,t}}_{\text{industry}} + \beta_3 \boldsymbol{X_{i,t}} + \epsilon_{i,e,j,t+1}, \tag{13}$$

where $r_{i,e,j,t+1}$ is the excess return of stock $i$ in ecoregion $e$ and industry $j$ in the next month $t+1$. The ecoregion and industry portfolios are measured in month $t$. The vector $\boldsymbol{X_{i,t}}$ contains the controls market beta, log(market capitalization), and the book-to-market ratio using the most recently available information as of June each year. Newey-West standard errors are used with a lag of 5.

# 3 Data

## 3.1 Geographical Data

We obtain Form 10-K and Form 10-KSB filings from the University of Notre Dame Software Repository for Accounting and Finance (SRAF) from 1993 to 2022. The state, zip code, and city name of each headquarters are extracted to create a dynamic measure of the location of the headquarters of a firm. Firms with headquarters outside the United States are excluded. Latitude and longitude coordinates are derived from the zip code[3] and matched to level 1, 2, and 3 ecoregion classifications using maps from the United States Environmental Protection Agency[4]. Each headquarters location is also associated with its state, census bureau region,

[3] Zip codes are linked to coordinates using https://www.unitedstateszipcodes.org/zip-code-database/.
[4] Available at: https://www.epa.gov/eco-research/ecoregions-north-america.

and census bureau division. For example, New York City is in the level 1 ecoregion Eastern Temperate Forests, the level 2 ecoregion Southeast Coastal Plains, the census bureau region known as the Northeast, and the census bureau division known as the Middle Atlantic.

We plan to obtain the National Establishment Time-Series (NETS) dataset that contains establishment-level data for public and private firms in the United States. The dataset has been used to assess the relationship between establishments, extreme temperature (Addoum et al., 2020), and hurricanes (Kruttli et al., 2024), and will provide us with granular information on a firms' geographical exposure to ecoregions.

We obtain tropical cyclone reports from the National Hurricane Center[5]. Shapefiles for each tropical and subtropical cyclone (including depressions, storms, and hurricanes) are used that contain the post-analysis best track of each cyclone. The shapefile includes points, lines, wind swath, and field radii. When a shapefile is not available, the information is parsed from the KMZ file. The start date is defined as the day the cyclone made landfall on the contiguous United States and is available in the points shapefile.

We obtain a high resolution (1km) map of habitat heterogeneity, a proxy of biodiversity, from Tuanmu and Jetz (2015)[6]. This dataset contains 14 metrics that quantify the spatial heterogeneity of global habitat. It uses the Enhanced Vegetation Index (EVI) based on imagery from the Moderate Resolution Imaging Spectroradiometer (MODIS). The homogeneity index shows the highest accuracy in predicting biodiversity, and beats competing measures based on topography features or land cover (Tuanmu and Jetz, 2015, Figure 4). We show that ecoregions capture this heterogeneity extremely well[7]. We also obtain shapefiles of ecoregion intactness from Beyer et al. (2020)[8]. These capture habitat loss, quality, and fragmentation effects and fit well with our focus on ecoregions.

[5]Available at: https://www.nhc.noaa.gov/data/tcr/index.php.
[6]Available at: https://www.earthenv.org/texture.
[7]For example, compare the map of "HOM1km" and ecoregion maps used in this paper. Available at: https://www.earthenv.org/texture.
[8]Available at: https://espace.library.uq.edu.au/view/UQ:f51cace.

### 3.2 Financial Data

Monthly stock returns, including delisting returns, are from CRSP for common stocks listed on either the NYSE, NASDAQ, or AMEX exchanges with information on headquarters location. Excess returns are calculated by subtracting the monthly risk-free rate from the monthly return. The risk-free rate is from Ken. French's Data Library. The market beta for each stock is estimated using a rolling regression of excess stock returns on the market factor using a window of 24 months and a minimum of 12 observations. The market factor is from Ken. French's Data Library.

The annual book-to-market ratio and market capitalization for each stock are calculated using data as of June each year from Compustat, following Fama and French (1993). Stocks with negative market capitalization are dropped, and the log of market capitalization is used. Total assets (investment), revenue (sales), and net income (cash flow) are from Compustat. The industry name for each stock is assigned using its SIC code, following Bali et al. (2016). The GICS sector code and sub-industry code are from Compustat.

## 4 Results

Our descriptive results show that firms are clustered across ecoregions. The majority are in three ecoregions at the level 2 scale: mixed wood plains (21%), southeastern plains (19%), and in Mediterranean California (19%). These regions have low ecological integrity as they have been affected by human development (Beyer et al., 2020). This result is symptomatic of the clustering of US industries in general (e.g., see Dougal et al., 2015), but we can now extend this result to nature. For example, more than 75% of the public firms in the United States are clustered in urban areas that constitute less than 1% of the land mass (Grieser et al., 2022). We plan to link the incidence of all firms in our sample with the integrity of ecoregions (Beyer et al., 2020) and their habitat heterogeneity (biodiversity) (Tuanmu and Jetz, 2015), and to assess their spatial distribution at the establishment level.

We then find that geographical effects, which have been identified in the extant literature, (Parsons et al., 2020; Smajlbegovic, 2019) do not stop at the city level or the state level.

Monthly contemporaneous returns have a sensitivity of 0.79 to an industry portfolio and a sensitivity of 0.22 to a level 2 ecoregion portfolio. For comparison, Parsons et al. (2020) identify an industry sensitivity of 0.90 and a city sensitivity of 0.30. This reveals that the effect of geography does not stop at municipalities. Instead, the geographical effect remains significant when portfolios are analyzed at the state, division, region, and various ecoregion scales. Similar results are found when we assess comovement in fundamentals at the ecoregion level.

The industry-effect, that is, the comovement with industry peers in other geographical areas, also does not seem to depend on how we scale the geographical area. We generally find the biggest industry effect size at the state scale and the ecoregion level 3 scale, suggesting this is more strongly correlated with industry formation.

The presence of economic links within ecoregions provides a new way to assess how firms relate to nature. However, do investors appreciate this connection? To answer this, we estimate monthly Fama-MacBeth regressions of individual stock returns on the *lagged* return of an equal-weighted industry portfolio that contains stocks outside of the ecoregion but within the same industry, alongside the *lagged* return of an equal-weighted ecoregion portfolio that contains stocks outside of each stock's industry but within the same ecoregion.

We find that the lagged level 2 and level 3 ecoregion portfolios can significantly predict returns, indicative of investor inattention. For example, a 1% increase in the level 2 ecoregion portfolio is associated with a 4 basis points increase in returns. This observation persists when the sample is stratified by firm size, a conventional measure of investor attention (Parsons et al., 2020; Groysberg et al., 2013; Lo and MacKinlay, 1990). This implies that the information is not fully incorporated in one period, but rather takes time to disseminate.

The observed inattention to ecoregions suggests that a trading strategy could, in theory, exist. The strategy only pays off if there is an information inefficiency, which is important for understanding how nature matters. Each month, we sort the ecoregions into quintiles based on their equal-weighted portfolio return to test this. We go long stocks that are in ecoregions with the highest momentum and short stocks in ecoregions with the lowest momentum, holding the stocks for one month. This is a standard momentum strategy only now applied

to ecoregions (e.g., see Jegadeesh and Titman, 2011). The long-short strategy leads to a significant six-factor risk-adjusted annualized return of 11.35% (t-stat=4.11) at the level 3 ecoregion level. However, we did not find significant alpha at the level 2 ecoregion level. We seek to explore this. Despite being a similar concept, we also find that the strategy is distinct from the momentum factor.

## 4.1 Mechanism

We subsequently delve into the underlying mechanisms driving the ecoregion lead-lag phenomenon. We exploit the random nature of hurricane tracks and the inherent buffering capacities of specific ecosystems. Coastal plains, for example, are particularly vulnerable to storm surges and intense winds because of their proximity to the ocean and low-lying topography. These areas are more susceptible to flooding, infrastructure damage, and business interruptions caused by hurricanes. In contrast, forested ecoregions can provide a degree of natural protection for firms. Forests act as windbreaks, reducing the impact of strong winds, and their dense vegetation can absorb significant amounts of rainwater, mitigating the risk of flooding. The protective characteristics of forested areas help protect firms from the immediate and severe impacts of hurricanes. This understanding allows us to better interpret the ecoregion lead-lag effect.

We assess stocks that are within 200 miles of the best track path of Hurricane Michael in 2018 – the first category 5 hurricane to make landfall since 1992. This is consistent with Kruttli et al. (2024), who use a similar threshold to assess the effect of hurricanes on uncertainty. Hurricane Michael presents a unique opportunity for analysis due to its trajectory, which does not traverse the United States from east to west. Hence, outcomes are less influenced by the strong correlation between longitude and ecoregions or the attenuating force of the hurricane as it progresses inland. We plot the mean cumulative excess return of stocks in each ecoregion from 30 days before landfall to 60 days after landfall. Our hypothesis is that the mean cumulative return should be different between ecoregions. The event window used is consistent with analogous studies, such as Kruttli et al. (2024), and suggests a notable divergence in returns between ecoregions. Importantly, we find that investment, sales, and

cash flow metrics do not significantly differ between ecoregions prior to Hurricane Michael's landfall, indicating that preexisting financial conditions do not bias the results.

# 5 Conclusion

We view nature as a geographical phenomenon. Once viewed in this manner, firms can be related to spatially-clustered ecological regions (ecoregions) to understand the linkage between economic activity and ecosystem services. We show that the performance and valuation of firms in similar ecoregions tend to comove and this effect is not fully incorporated into stock prices. Our approach avoids having to measure some form of nature dependence at the firm-level, and instead relies on scientific consensus that nature is complex yet can be grouped into regions with varying levels of productivity.

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Table 1: Stocks per industry. This table reports the number of stocks per industry for the final sample. Industry is defined using the SIC code, following Bali et al. (2016).

| Industry | Count |
|---|---|
| Manufacturing | 3,966 |
| Services | 1,957 |
| Finance | 1,573 |
| Retail | 542 |
| Transportation | 467 |
| Mining | 385 |
| Wholesale | 276 |
| Utilities | 223 |
| Construction | 93 |
| Public | 71 |
| Agriculture | 28 |
| Total | 9,601 |

Table 2: Contemporaneous comovement in investment. This table reports results of panel regressions of individual firms' annual change in investment on the contemporaneous mean annual change in investment for firms located in the same geography but in different industries ("Geography") and on the contemporaneous mean of the annual change in investment for firms located in the same industry but in different geographies ("Industry"). The sample period is 1996 - 2022. Investment is measured as the period-by-period change in total assets and is winsorized at the 1% and 99% level. A minimum of 6 industries must exist in each geography and a minimum of 6 firms must exist in each industry. Regressions include firm fixed effects.

| | Annual $\Delta$ investment | | | | | | |
|---|---|---|---|---|---|---|---|
| | City | State | Divison | Region | Ecoregion L1 | Ecoregion L2 | Ecoregion L3 |
| Geography | -0.00 | 0.020** | 0.065*** | 0.102*** | 0.150*** | 0.091*** | 0.046*** |
| | (-0.76) | (2.18) | (2.80) | (3.64) | (4.65) | (4.27) | (2.77) |
| Industry | 0.333* | 0.509*** | 0.450*** | 0.378*** | 0.225* | 0.462*** | 0.491*** |
| | (1.75) | (3.07) | (2.90) | (2.77) | (1.72) | (2.79) | (2.96) |
| $R^2$ (%) | 0.14 | 0.19 | 0.16 | 0.14 | 0.07 | 0.17 | 0.19 |
| Obs. | 18,499 | 60,570 | 65,110 | 65,478 | 65,126 | 64,392 | 59,197 |
| Firm FE | Y | Y | Y | Y | Y | Y | Y |
| Firm clusters | 2,282 | 7,686 | 8,113 | 8,150 | 8,128 | 8,042 | 7,539 |

* $p < .10$, ** $p < .05$, *** $p < .01$. Robust t-statistics in parentheses. Intercept omitted.

Table 3: Contemporaneous comovement in sales. This table reports results of panel regressions of individual firms' annual change in sales on the contemporaneous mean of the annual change in sales for firms located in the same geography but in different industries ("Geography") and on the contemporaneous mean of the annual change in sales for firms located in the same industry but in different geographies ("Industry"). The sample period is 1996 - 2022. Sales is measured as the period-by-period change in revenue and is winsorized at the 1% and 99% level. A minimum of 6 industries must exist in each geography and a minimum of 6 firms must exist in each industry. Regressions include firm fixed effects.

| | Annual $\Delta$ sales | | | | | | |
|---|---|---|---|---|---|---|---|
| | City | State | Divison | Region | Ecoregion L1 | Ecoregion L2 | Ecoregion L3 |
| Geography | 0.017 | 0.196*** | 0.405*** | 0.533*** | 0.608*** | 0.355** | 0.160*** |
| | (1.14) | (3.10) | (4.24) | (5.66) | (3.86) | (2.56) | (2.75) |
| Industry | 0.598*** | 0.706*** | 0.636*** | 0.337*** | 0.202** | 0.650*** | 0.706*** |
| | (6.41) | (9.56) | (10.08) | (3.14) | (2.15) | (8.89) | (10.23) |
| $R^2$ (%) | 1.28 | 1.48 | 1.62 | 1.08 | 1.30 | 1.74 | 1.34 |
| Obs. | 18,499 | 60,570 | 65,109 | 65,477 | 65,125 | 64,391 | 59,197 |
| Firm FE | Y | Y | Y | Y | Y | Y | Y |
| Firm clusters | 2,282 | 7,686 | 8,113 | 8,150 | 8,128 | 8,042 | 7,539 |

* $p < .10$, ** $p < .05$, *** $p < .01$. Robust t-statistics in parentheses. Intercept omitted.

Table 4: Contemporaneous comovement in cash flow. This table reports results of panel regressions of individual firms' annual change in cash flow on the contemporaneous mean of the annual change in cash flow for firms located in the same geography but in different industries ("Geography") and on the contemporaneous mean of the annual change in cash flow for firms located in the same industry but in different geographies ("Industry"). The sample period is 1996 - 2022. Cash flow is measured as the period-by-period change in net income and is winsorized at the 1% and 99% level. A minimum of 6 industries must exist in each geography and a minimum of 6 firms must exist in each industry. Regressions include firm fixed effects.

| | Annual $\Delta$ cash flow | | | | | | |
|---|---|---|---|---|---|---|---|
| | City | State | Divison | Region | Ecoregion L1 | Ecoregion L2 | Ecoregion L3 |
| Geography | 0.170*** | 0.220*** | 0.356*** | 0.559*** | 0.701*** | 0.317*** | 0.192*** |
| | (3.16) | (3.90) | (4.87) | (7.01) | (6.42) | (3.41) | (3.55) |
| Industry | 0.444*** | 0.686*** | 0.602*** | 0.166* | 0.082 | 0.675*** | 0.706*** |
| | (5.41) | (6.11) | (5.78) | (1.81) | (1.22) | (5.82) | (5.64) |
| $R^2$ (%) | 0.91 | 1.32 | 1.14 | 0.61 | 0.79 | 1.38 | 1.32 |
| Obs. | 18,499 | 60,570 | 65,109 | 65,477 | 65,125 | 64,391 | 59,197 |
| Firm FE | Y | Y | Y | Y | Y | Y | Y |
| Firm clusters | 2,282 | 7,686 | 8,113 | 8,150 | 8,128 | 8,042 | 7,539 |

* $p < .10$, ** $p < .05$, *** $p < .01$. Robust t-statistics in parentheses. Intercept omitted.

Table 5: Contemporaneous comovement in excess returns. This table reports results of panel regressions of individual firms' monthly excess returns on a contemporaneous equal-weighted portfolio of firms located in the same geography but in different industries ("Geography") and on a contemporaneous equal-weighted portfolio of firms located in the same industry but in different geographies ("Industry"). The sample period is 1996 - 2022. Returns are not winsorized. A minimum of 6 industries must exist in each geography and a minimum of 6 firms must exist in each industry. Regressions include firm fixed effects.

| | Monthly contemporaneous excess return | | | | | | |
|---|---|---|---|---|---|---|---|
| | City | State | Divison | Region | Ecoregion L1 | Ecoregion L2 | Ecoregion L3 |
| Geography | 0.117*** | 0.192*** | 0.285*** | 0.309*** | 0.330*** | 0.215*** | 0.183*** |
| | (11.31) | (19.98) | (21.91) | (22.09) | (26.04) | (15.57) | (15.87) |
| Industry | 0.837*** | 0.807*** | 0.734*** | 0.706*** | 0.647*** | 0.790*** | 0.816*** |
| | (54.00) | (69.17) | (52.58) | (47.48) | (50.55) | (54.44) | (57.07) |
| $R^2$ (%) | 14.19 | 13.12 | 13.19 | 13.00 | 12.75 | 13.22 | 13.16 |
| Obs. | 262,032 | 785,953 | 837,694 | 842,248 | 839,768 | 833,971 | 774,573 |
| Firm FE | Y | Y | Y | Y | Y | Y | Y |
| Firm clusters | 2,972 | 9,045 | 9,505 | 9,553 | 9,533 | 9,473 | 8,964 |

* $p < .10$, ** $p < .05$, *** $p < .01$. Robust t-statistics in parentheses. Intercept omitted.

Table 6: Fama MacBeth regressions over 1996 - 2022. This table reports results of monthly Fama MacBeth regressions of excess stock returns on a lagged equal-weighted portfolio of firms located in the same geography but in different industries ("Geography") and on a lagged equal-weighted portfolio of firms located in the same industry but in different geographies ("Industry"). The sample period is 1996 - 2022. The controls are market beta, the book-to-market ratio, and log(market capitalization). Standard errors are adjusted following Newey and West (1987) using a data-driven lag of $4(T/100)^{2/9}$ (i.e., the Bartlett kernel), where $T$ is the number of periods (Bali et al., 2016).

| | Monthly 1-month predictive excess return | | | | | | |
|---|---|---|---|---|---|---|---|
| | City | State | Divison | Region | Ecoregion L1 | Ecoregion L2 | Ecoregion L3 |
| Geography | 0.011 | 0.024** | 0.043* | 0.020 | 0.03 | 0.038** | 0.020** |
| | (1.62) | (2.48) | (1.91) | (0.59) | (1.62) | (2.37) | (2.42) |
| Industry | 0.075*** | 0.113*** | 0.129*** | 0.118*** | 0.104*** | 0.117*** | 0.103*** |
| | (2.76) | (4.46) | (5.34) | (5.27) | (5.07) | (4.92) | (4.27) |
| Av. $R^2$ (%) | 10.54 | 9.60 | 9.63 | 9.59 | 9.59 | 9.61 | 9.55 |
| Obs. | 248,140 | 745,655 | 795,404 | 799,822 | 797,328 | 791,700 | 734,542 |

* $p < .10$, ** $p < .05$, *** $p < .01$. Newey West standard errors using 5 lags with t-statistics in parentheses. Intercept and controls omitted.

Table 7: Fama MacBeth with size quintiles for level 2 and level 3 ecoregions. This table reports results of monthly Fama MacBeth regressions of excess stock returns on a lagged equal-weighted portfolio of firms located in the same geography but in different industries ("Geography") and on a lagged equal-weighted portfolio of firms located in the same industry but in different geographies ("Industry"). The sample period is 1996 - 2022. The controls are market beta, the book-to-market ratio, and log(market capitalization). Standard errors are adjusted following Newey and West (1987) using a data-driven lag of $4(T/100)^{2/9}$ (i.e., the Bartlett kernel), where $T$ is the number of periods (Bali et al., 2016).

| | Ecoregion L2 | | | | | Ecoregion L3 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Small | 2 | 3 | 4 | Big | Small | 2 | 3 | 4 | Big |
| Geography | -0.012 | 0.046* | 0.044* | 0.038* | 0.055*** | 0.004 | 0.032** | 0.012 | 0.022* | 0.026** |
| | (-0.28) | (1.78) | (1.77) | (1.88) | (2.80) | (0.21) | (2.20) | (0.84) | (1.80) | (2.49) |
| Industry | 0.203*** | 0.147*** | 0.109*** | 0.089*** | 0.054** | 0.142*** | 0.117*** | 0.132*** | 0.077** | 0.036 |
| | (4.81) | (3.89) | (3.35) | (3.04) | (2.21) | (3.01) | (2.88) | (3.84) | (2.51) | (1.43) |
| Av. $R^2$ (%) | 10.13 | 10.00 | 10.76 | 12.35 | 15.39 | 10.54 | 9.90 | 10.82 | 12.32 | 15.24 |
| Obs. | 153,863 | 156,873 | 158,775 | 160,399 | 161,790 | 142,790 | 145,573 | 147,401 | 148,763 | 150,015 |

* $p < .10$, ** $p < .05$, *** $p < .01$.

t-statistics with Newey West standard errors using 5 lags in parentheses.

Intercept and controls omitted.

Table 8: Fama MacBeth with size quintiles for level 1 ecoregions. This table reports results of monthly Fama MacBeth regressions of excess stock returns on a lagged equal-weighted portfolio of firms located in the same geography but in different industries ("Geography") and on a lagged equal-weighted portfolio of firms located in the same industry but in different geographies ("Industry"). The sample period is 1996 - 2022. The controls are market beta, the book-to-market ratio, and log(market capitalization). Standard errors are adjusted following Newey and West (1987) using a data-driven lag of $4(T/100)^{2/9}$ (i.e., the Bartlett kernel), where $T$ is the number of periods (Bali et al., 2016).

| | Ecoregion L1 | | | | |
|---|---|---|---|---|---|
| | Small | 2 | 3 | 4 | Big |
| Geography | -0.034 | 0.034 | 0.033 | 0.052* | 0.069** |
| | (-0.55) | (0.93) | (0.91) | (1.82) | (2.51) |
| Industry | 0.155*** | 0.137*** | 0.091*** | 0.085*** | 0.040** |
| | (3.31) | (4.16) | (3.20) | (3.41) | (1.97) |
| Av. $R^2$ (%) | 10.28 | 10.06 | 10.66 | 12.25 | 15.30 |
| Obs. | 154,969 | 157,953 | 159,915 | 161,551 | 162,940 |

* $p < .10$, ** $p < .05$, *** $p < .01$.

t-statistics with Newey West standard errors using 5 lags in parentheses.

Intercept and controls omitted.

Table 9: Nature-based trading strategy. This table reports the mean return and the Fama French six factor adjusted return (FF6-$\alpha$) for equal-weighted quintile portfolios over the period 1996 - 2022. Each month, stocks are sorted into quintile portfolios by the average lagged return of firms headquartered in the same ecoregion but in different industries. The high minus low strategy is then long stocks in the highest (ecoregion-momentum) quintile and short stocks in the lowest (ecoregion-momentum) quintile. The holding period is 1-month.

| | Ecoregion L2 quintiles | | | Ecoregion L3 quintiles | | |
|---|---|---|---|---|---|---|
| | Mean | FF6-$\alpha$ | t-stat | Mean | FF6-$\alpha$ | t-stat |
| Lowest ecoregion momentum | 0.013 | 0.013*** | 5.13 | 0.014 | 0.015*** | 5.47 |
| 2 | 0.008 | 0.010*** | 3.52 | 0.009 | 0.011*** | 4.48 |
| 3 | 0.010 | 0.011*** | 4.36 | 0.011 | 0.013*** | 4.80 |
| 4 | 0.012 | 0.013*** | 4.92 | 0.011 | 0.012*** | 4.04 |
| Highest ecoregion momentum | 0.009 | 0.009*** | 3.22 | 0.006 | 0.006** | 2.57 |
| High - low | 0.004 | 0.004 | 1.59 | 0.008 | 0.009*** | 4.11 |

* $p < .10$, ** $p < .05$, *** $p < .01$.

t-statistics with Newey West standard errors using 5 lags.

Table 10: Summary statistics at the level 1 ecoregion level. This table reports summary statistics at the level 1 ecoregion level and is sorted by firm size Size is measured as log(market capitalization). Count is the historical count of stocks that have ever been headquartered in the ecoregion. An ecoregion must have least six stocks to be included.

| Level 1 Ecoregion | Return | Beta | Size | B-M | Total Assets | Revenue | Net Income | Count |
|---|---|---|---|---|---|---|---|---|
| Eastern Temperate Forests | 0.009 | 1.141 | 13.200 | 0.735 | 10434.912 | 3648.875 | 230.277 | 5,678 |
| Great Plains | 0.009 | 1.264 | 13.195 | 0.813 | 6347.764 | 3737.867 | 201.348 | 1,429 |
| Marine West Coast Forest | 0.012 | 1.435 | 13.158 | 0.633 | 7410.889 | 5614.845 | 669.643 | 284 |
| Mediterranean California | 0.011 | 1.474 | 13.046 | 0.593 | 4764.895 | 2018.568 | 143.422 | 1,978 |
| North American Deserts | 0.009 | 1.267 | 12.862 | 0.722 | 2925.693 | 1654.518 | 81.904 | 381 |
| Northwestern Forested Mountains | 0.007 | 1.107 | 12.721 | 0.761 | 2607.962 | 3449.425 | 117.260 | 127 |
| Tropical Wet Forests | 0.009 | 1.237 | 12.611 | 0.808 | 2974.621 | 2124.438 | 79.349 | 220 |
| Northern Forests | 0.003 | 1.009 | 11.593 | 0.806 | 1196.984 | 218.331 | 4.922 | 49 |

Table 11: Summary statistics at the level 2 ecoregion level. This table reports summary statistics at the level 2 ecoregion level and is sorted by firm size. Size is measured as log(market capitalization). Count is the historical count of stocks that have ever been headquartered in the ecoregion. An ecoregion must have least six stocks to be included.

| Level 2 Ecoregion | Return | Beta | Size | B-M | Total Assets | Revenue | Net Income | Count |
|---|---|---|---|---|---|---|---|---|
| Central Plains | 0.009 | 1.129 | 13.557 | 0.727 | 7728.076 | 4717.810 | 241.976 | 821 |
| Temperate Prairies | 0.011 | 1.111 | 13.473 | 0.797 | 11450.039 | 3761.882 | 341.017 | 192 |
| Ozark/Ouachita-Appalachian Forests | 0.009 | 1.044 | 13.341 | 0.793 | 7756.166 | 5503.708 | 222.524 | 360 |
| Texas-Louisiana Coastal Plain | 0.008 | 1.341 | 13.340 | 0.851 | 4924.451 | 3524.867 | 103.044 | 398 |
| Southeastern Plains | 0.009 | 1.113 | 13.183 | 0.733 | 10180.055 | 3461.107 | 226.156 | 1992 |
| Mixed Wood Plains | 0.010 | 1.208 | 13.181 | 0.705 | 14112.865 | 3496.496 | 260.253 | 2232 |
| Marine West Coast Forest | 0.012 | 1.435 | 13.158 | 0.633 | 7410.889 | 5614.845 | 669.643 | 284 |
| Warm Deserts | 0.010 | 1.329 | 13.117 | 0.692 | 3124.484 | 1889.451 | 101.204 | 244 |
| Mediterranean California | 0.011 | 1.474 | 13.046 | 0.593 | 4764.895 | 2018.568 | 143.422 | 1978 |
| South Central Semi-arid Prairies | 0.009 | 1.279 | 13.045 | 0.794 | 5542.898 | 3896.580 | 209.901 | 866 |
| West Central Semi-arid Prairies | 0.006 | 0.956 | 12.835 | 1.012 | 3152.017 | 1109.905 | 61.330 | 14 |
| Western Cordillera | 0.007 | 1.107 | 12.721 | 0.761 | 2607.962 | 3449.425 | 117.260 | 127 |
| Mississippi Alluvial & Southeast Coastal Plains | 0.008 | 1.079 | 12.671 | 0.826 | 3724.563 | 1889.495 | 119.949 | 624 |
| Everglades | 0.009 | 1.237 | 12.611 | 0.808 | 2974.621 | 2124.438 | 79.349 | 220 |
| Cold Deserts | 0.008 | 1.161 | 12.422 | 0.773 | 2583.153 | 1249.698 | 48.648 | 143 |
| Mixed Wood Shield | 0.002 | 1.327 | 11.623 | 0.967 | 297.480 | 95.761 | 4.378 | 10 |
| Atlantic Highlands | 0.004 | 0.969 | 11.590 | 0.785 | 1309.167 | 233.618 | 4.990 | 39 |

Table 12: Summary statistics at the level 3 ecoregion level. This table reports summary statistics at the level 3 ecoregion level and is sorted by firm size. Size is measured as log(market capitalization). Count is the historical count of stocks that have ever been headquartered in the ecoregion. An ecoregion must have least six stocks to be included.

| Level 3 Ecoregion | Return | Beta | Size | B-M | Total Assets | Revenue | Net Income | Count |
|---|---|---|---|---|---|---|---|---|
| Idaho Batholith | 0.012 | 1.258 | 15.200 | 0.823 | 9713.854 | 5514.288 | 742.055 | 6 |
| Cascades | 0.009 | 0.892 | 15.140 | 0.445 | 13410.915 | 43828.041 | 844.027 | 6 |
| Ozark Highlands | 0.012 | 0.726 | 14.108 | 0.676 | 17074.105 | 37309.657 | 1209.533 | 23 |
| Mississippi Alluvial Plain | 0.004 | 1.044 | 13.810 | 1.127 | 8184.408 | 2755.270 | 161.454 | 36 |
| Western Corn Belt Plains | 0.010 | 1.055 | 13.805 | 0.774 | 17215.746 | 5237.815 | 589.510 | 97 |
| Southeastern Wisconsin Till Plains | 0.010 | 1.079 | 13.798 | 0.647 | 5069.622 | 2958.769 | 244.788 | 125 |
| Mississippi Valley Loess Plains | 0.011 | 1.082 | 13.669 | 0.722 | 6936.927 | 5378.596 | 213.960 | 43 |
| Interior Plateau | 0.010 | 0.982 | 13.643 | 0.717 | 6972.811 | 6032.826 | 355.735 | 171 |
| Central Corn Belt Plains | 0.008 | 1.142 | 13.634 | 0.713 | 7511.029 | 4139.423 | 243.775 | 390 |
| Interior River Valleys and Hills | 0.009 | 1.073 | 13.633 | 0.755 | 6090.186 | 3659.659 | 196.562 | 123 |
| Chihuahuan Deserts | 0.004 | 0.765 | 13.619 | 0.894 | 2200.090 | 2795.241 | 74.831 | 6 |
| Snake River Plain | 0.007 | 1.362 | 13.607 | 0.664 | 3173.946 | 6257.181 | 132.111 | 17 |
| Central Great Plains | 0.008 | 1.242 | 13.587 | 0.812 | 6231.340 | 2230.062 | 25.050 | 51 |
| Huron/Erie Lake Plains | 0.008 | 1.275 | 13.521 | 0.815 | 17751.737 | 10569.147 | 328.760 | 102 |
| Middle Atlantic Coastal Plain | 0.007 | 1.058 | 13.436 | 0.830 | 8943.823 | 3837.501 | 324.607 | 127 |
| Central California Foothills and Coastal Mountains | 0.013 | 1.628 | 13.399 | 0.520 | 7172.287 | 2767.099 | 216.740 | 1057 |
| Ridge and Valley | 0.008 | 1.051 | 13.368 | 0.767 | 6353.849 | 2317.330 | 117.293 | 172 |
| Southern Michigan/Northern Indiana Drift Plains | 0.007 | 1.069 | 13.363 | 0.783 | 3537.672 | 2650.996 | 133.597 | 104 |
| Western Allegheny Plateau | 0.010 | 1.168 | 13.348 | 0.774 | 8658.327 | 2186.982 | 142.328 | 126 |
| Western Gulf Coastal Plain | 0.008 | 1.341 | 13.340 | 0.851 | 4924.451 | 3524.867 | 103.044 | 398 |
| Arkansas Valley | 0.017 | 1.253 | 13.339 | 0.966 | 3414.317 | 2194.149 | 89.159 | 9 |
| Puget Lowland | 0.012 | 1.403 | 13.338 | 0.588 | 9067.253 | 6656.940 | 633.111 | 168 |
| Southeastern Plains | 0.009 | 0.889 | 13.314 | 0.806 | 7221.859 | 2080.245 | 191.620 | 206 |
| Eastern Corn Belt Plains | 0.010 | 1.066 | 13.274 | 0.766 | 5015.169 | 4124.012 | 195.144 | 214 |
| Erie Drift Plain | 0.008 | 1.162 | 13.266 | 0.854 | 4140.006 | 2710.895 | 117.233 | 90 |
| Northern Allegheny Plateau | 0.010 | 1.044 | 13.261 | 0.812 | 5516.221 | 1477.146 | 198.513 | 17 |
| Northeastern Coastal Zone | 0.010 | 1.253 | 13.231 | 0.689 | 18287.107 | 3755.669 | 300.355 | 1671 |
| Cross Timbers | 0.005 | 1.260 | 13.223 | 0.941 | 3199.941 | 1610.116 | 83.674 | 73 |
| Coast Range | 0.020 | 1.888 | 13.203 | 0.631 | 16046.901 | 12712.424 | 2583.866 | 36 |
| Texas Blackland Prairies | 0.010 | 1.218 | 13.168 | 0.817 | 8291.928 | 6423.380 | 394.411 | 398 |
| Sonoran Basin and Range | 0.011 | 1.328 | 13.129 | 0.673 | 2764.046 | 1989.285 | 119.800 | 152 |
| Central Irregular Plains | 0.012 | 1.180 | 13.096 | 0.824 | 4759.668 | 2094.354 | 41.984 | 87 |
| South Central Plains | 0.011 | 1.168 | 13.086 | 0.772 | 3794.743 | 1881.061 | 49.811 | 56 |

Table 13: Summary statistics at the level 3 ecoregion level continued. This table reports summary statistics at the level 3 ecoregion level and is sorted by firm size. Size is measured as log(market capitalization). Count is the historical count of stocks that have ever been headquartered in the ecoregion. An ecoregion must have least six stocks to be included.

| Level 3 Ecoregion | Return | Beta | Size | B-M | Total Assets | Revenue | Net Income | Count |
|---|---|---|---|---|---|---|---|---|
| North Central Hardwood Forests | 0.009 | 1.204 | 13.065 | 0.623 | 8151.354 | 4668.360 | 289.503 | 235 |
| Piedmont | 0.008 | 1.119 | 13.060 | 0.781 | 16152.790 | 3677.134 | 274.695 | 605 |
| Mojave Basin and Range | 0.008 | 1.378 | 13.050 | 0.714 | 3944.935 | 1607.390 | 65.124 | 90 |
| Northern Piedmont | 0.010 | 1.207 | 13.014 | 0.673 | 8814.357 | 3019.741 | 188.377 | 873 |
| Sierra Nevada | 0.011 | 0.878 | 13.000 | 0.787 | 1922.971 | 635.547 | 70.674 | 13 |
| Eastern Great Lakes Lowlands | 0.009 | 1.034 | 12.868 | 0.760 | 4794.981 | 1363.106 | 101.740 | 123 |
| High Plains | 0.008 | 1.332 | 12.841 | 0.751 | 2776.339 | 1461.757 | 26.607 | 300 |
| Willamette Valley | 0.009 | 1.345 | 12.835 | 0.709 | 1845.652 | 1580.327 | 122.949 | 82 |
| Driftless Area | 0.013 | 0.958 | 12.785 | 0.834 | 1379.272 | 758.847 | 72.285 | 12 |
| Wasatch and Uinta Mountains | 0.006 | 1.122 | 12.717 | 0.527 | 1097.104 | 1092.476 | 13.535 | 28 |
| Southern California/Northern Baja Coast | 0.010 | 1.307 | 12.689 | 0.661 | 2131.979 | 1209.312 | 64.936 | 903 |
| Northwestern Great Plains | 0.004 | 1.284 | 12.649 | 1.166 | 3318.959 | 603.555 | 48.727 | 10 |
| Southern Coastal Plain | 0.008 | 1.111 | 12.631 | 0.794 | 2476.849 | 1642.305 | 79.147 | 278 |
| Southern Florida Coastal Plain | 0.009 | 1.237 | 12.611 | 0.808 | 2974.621 | 2124.438 | 79.349 | 220 |
| Edwards Plateau | 0.011 | 1.517 | 12.593 | 0.664 | 1173.274 | 1216.793 | 24.079 | 70 |
| Lake Agassiz Plain | 0.018 | 1.222 | 12.584 | 1.096 | 894.255 | 842.589 | 15.994 | 7 |
| Northern Rockies | 0.007 | 1.136 | 12.517 | 0.824 | 1785.816 | 585.849 | 9.793 | 25 |
| Southern California Mountains | 0.011 | 1.385 | 12.507 | 0.726 | 906.066 | 887.968 | -2.994 | 15 |
| Central Basin and Range | 0.010 | 1.146 | 12.499 | 0.773 | 2797.065 | 873.713 | 48.080 | 96 |
| North Central Appalachians | -0.001 | 0.940 | 12.496 | 0.769 | 4094.535 | 788.977 | 33.843 | 7 |
| Southwestern Tablelands | 0.022 | 1.520 | 12.400 | 0.592 | 959.275 | 608.545 | 39.989 | 10 |
| Blue Ridge | 0.007 | 0.616 | 12.320 | 1.169 | 3255.821 | 960.319 | 29.729 | 11 |
| Middle Rockies | 0.001 | 0.892 | 12.079 | 0.684 | 879.713 | 258.954 | 25.473 | 10 |
| Atlantic Coastal Pine Barrens | 0.009 | 1.059 | 12.042 | 0.812 | 1236.711 | 828.212 | 35.792 | 194 |
| Columbia Plateau | 0.001 | 1.024 | 11.986 | 0.819 | 2504.537 | 170.741 | 17.550 | 7 |
| Central Appalachians | 0.010 | 0.650 | 11.922 | 1.006 | 1900.780 | 109.644 | 18.244 | 7 |
| Acadian Plains and Hills | 0.008 | 0.711 | 11.726 | 0.925 | 1473.356 | 80.973 | 14.655 | 7 |
| Arizona/New Mexico Plateau | -0.001 | 1.209 | 11.630 | 0.828 | 1447.013 | 488.252 | 15.319 | 18 |
| Southwestern Appalachians | 0.012 | 0.959 | 11.551 | 1.264 | 338.773 | 359.773 | 19.023 | 9 |
| Southern Rockies | 0.002 | 1.170 | 11.513 | 0.879 | 761.913 | 464.644 | 20.444 | 36 |
| Central California Valley | 0.002 | 1.058 | 11.459 | 1.172 | 659.478 | 376.333 | -21.806 | 32 |
| Northeastern Highlands | 0.004 | 0.974 | 11.415 | 0.788 | 773.181 | 126.750 | -0.562 | 32 |
| Northern Lakes and Forests | 0.001 | 1.159 | 11.000 | 1.208 | 258.118 | 73.550 | 4.784 | 9 |

# Figures

Figure 2: Number of stocks per level 1 ecoregion.

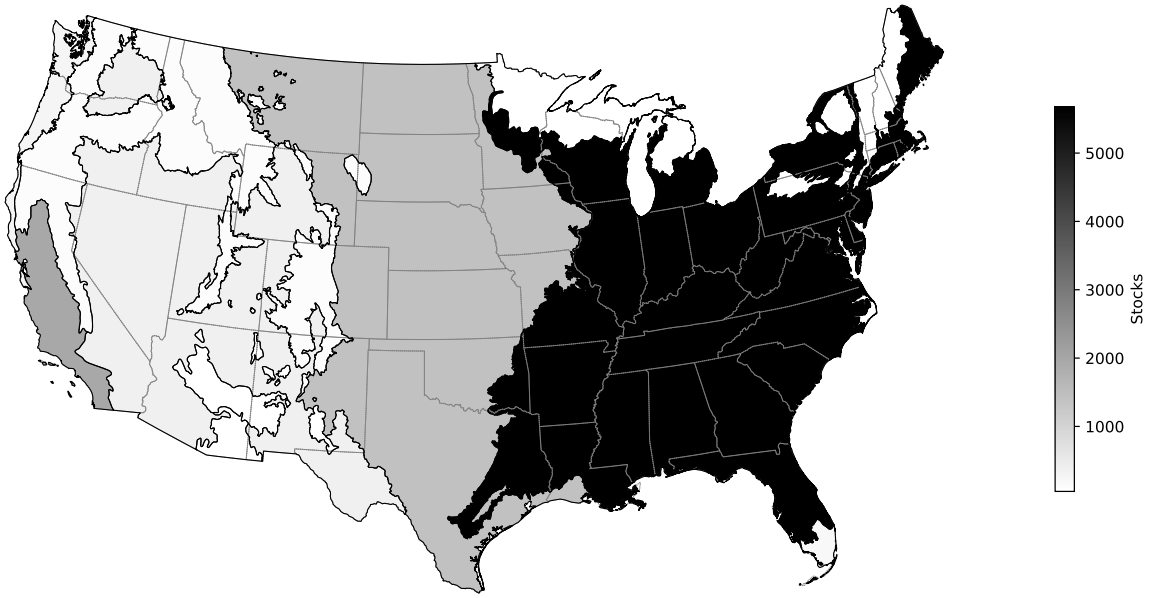


Figure 3: Number of stocks per level 2 ecoregion.

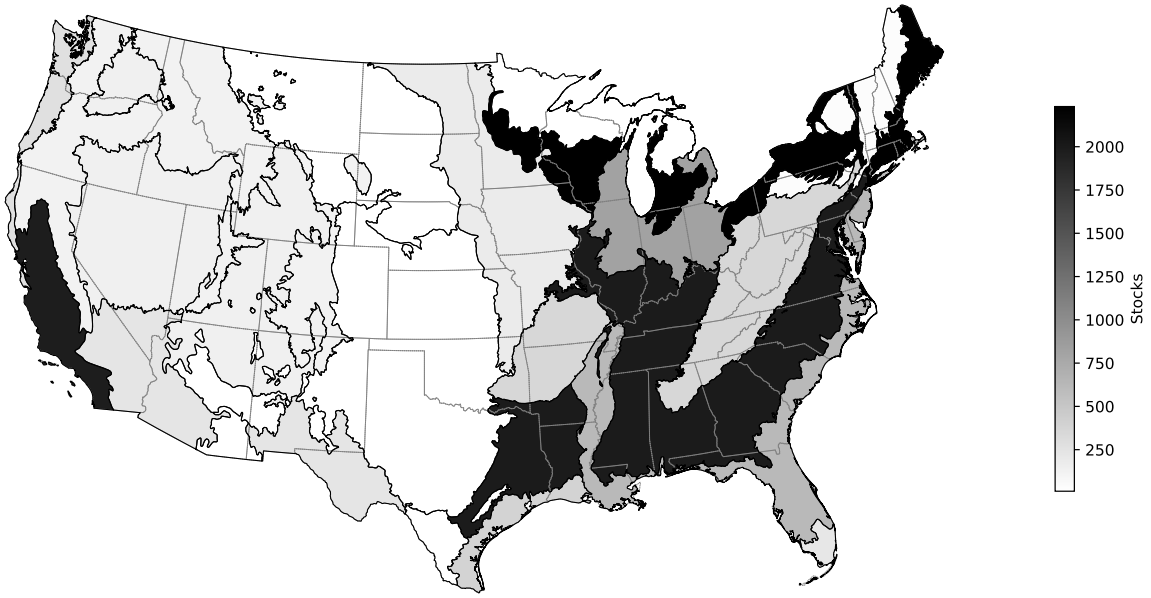


Figure 4: Number of stocks per level 3 ecoregion.



Figure 5: Level 1 ecoregions. This figure plots level 1 ecoregions with selected labels. The average size of level 1 ecoregions is 707,827 $km^2$. For comparison, the greater New York area is 9,332 $km^2$.

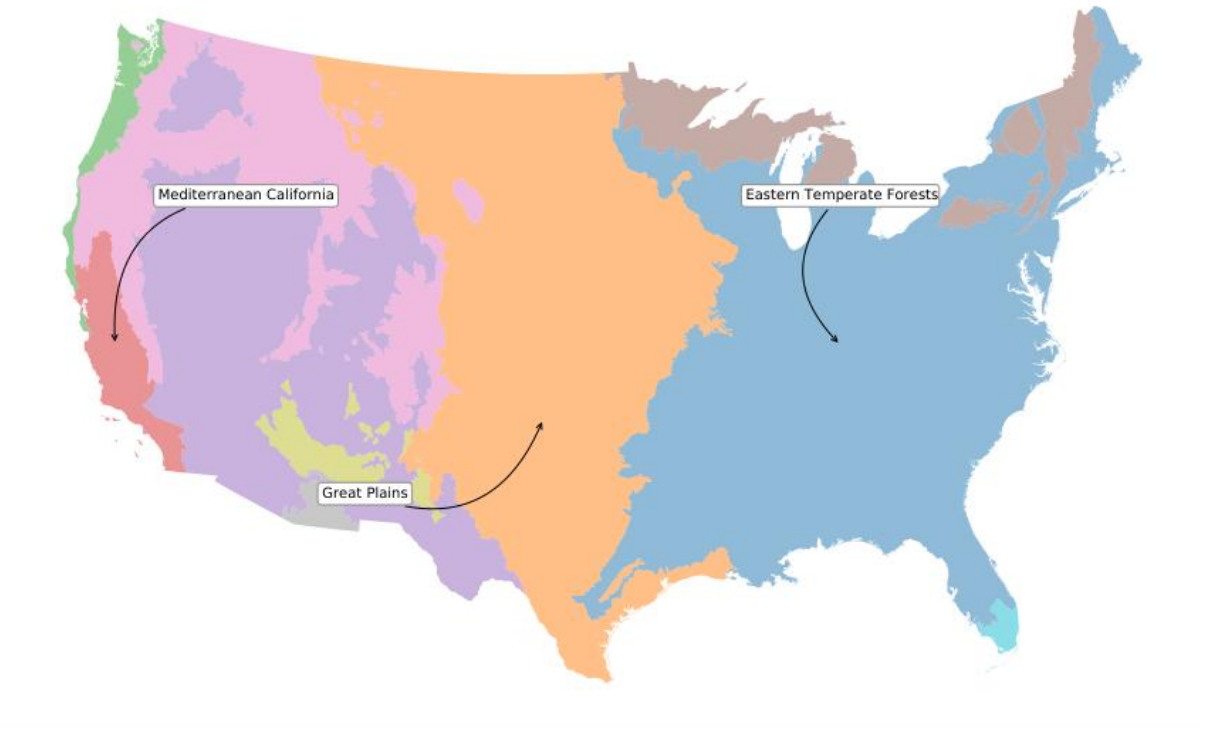


Figure 6: Level 2 ecoregions. This figure plots level 2 ecoregions with selected labels. The average size of level 2 ecoregions is 370,766 $km^2$. For comparison, the greater New York area is 9,332 $km^2$.

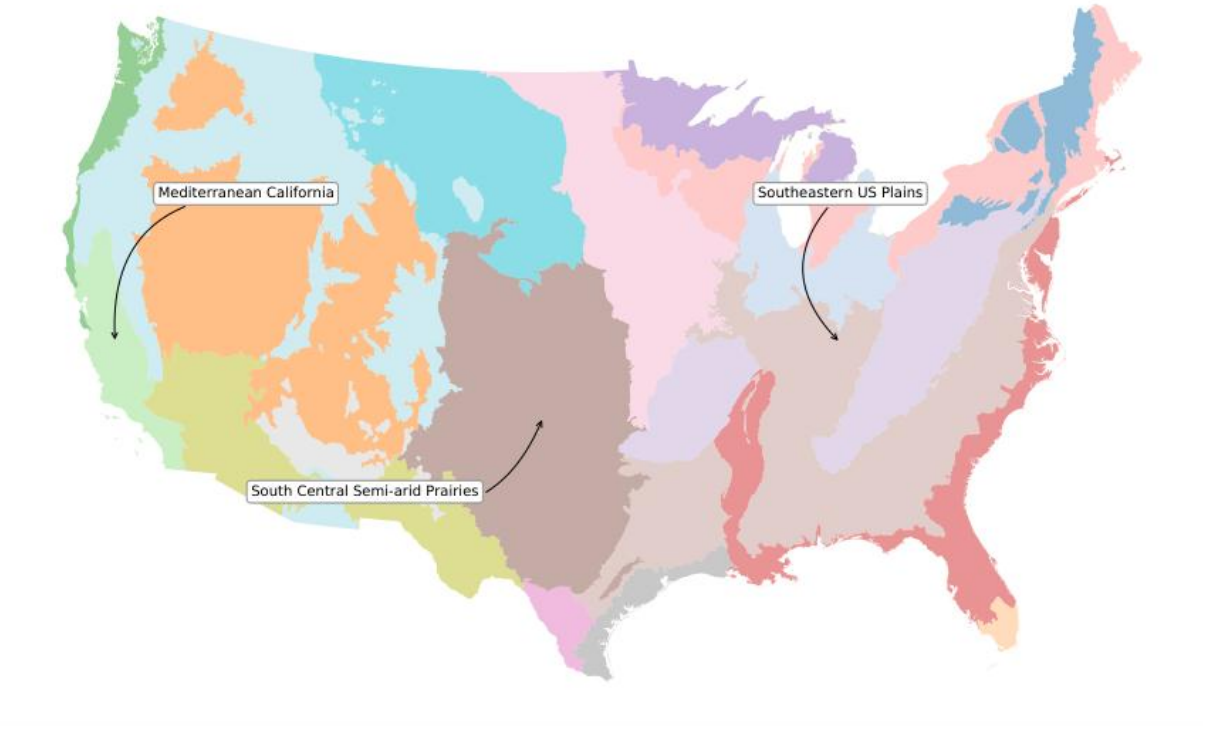


Figure 7: Level 3 ecoregions. This figure plots level 3 ecoregions with selected labels. The average size of level 3 ecoregions is 89,495 km$^2$. For comparison, the greater New York area is 9,332 km$^2$.



Figure 8: Geographical boundaries. This figure plots metropolitan area, region, division, and level 1 ecoregion boundaries.

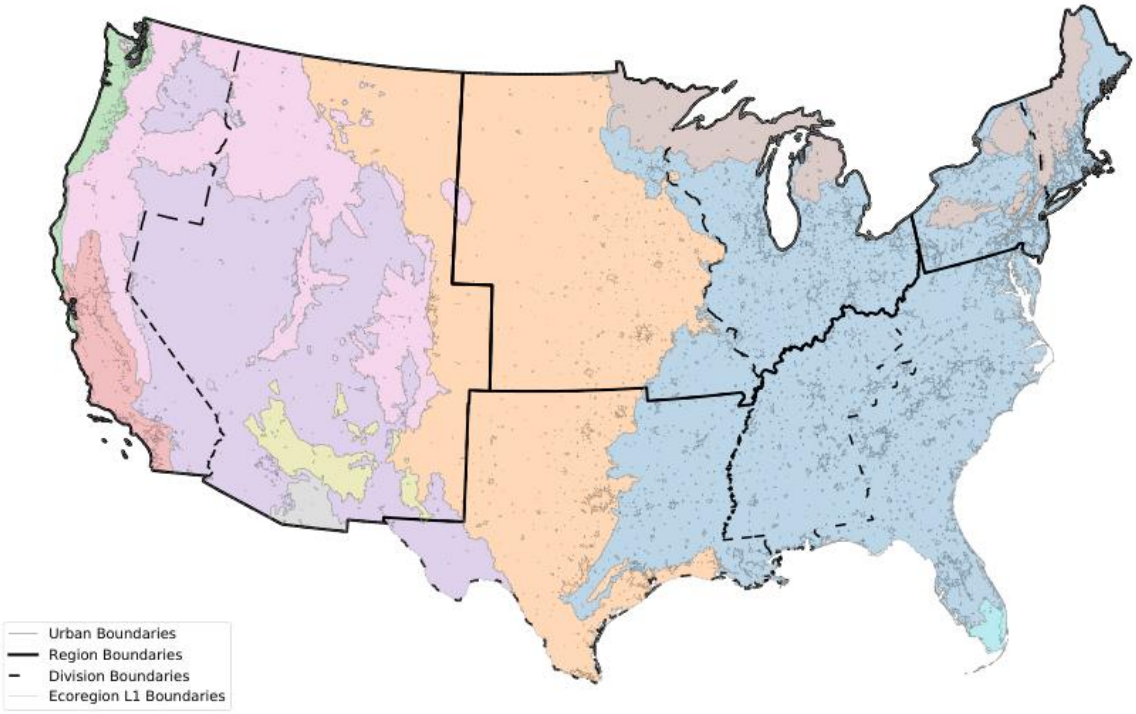


Figure 9: Cumulative return of the nature-based trading strategy. This figure plots the cumulative excess return of the momentum-based ecoregion trading strategy. Each month, ecoregions are sorted into quintiles based on their equal-weighted return. The strategy is long stocks in the highest momentum ecoregion and short stocks in the lowest momentum ecoregion and the holding period is 1 month. MKTRF is the market factor. SMB is the size factor. HML is the value factor. RMW is the profitability factor. CMA is the investment factor.

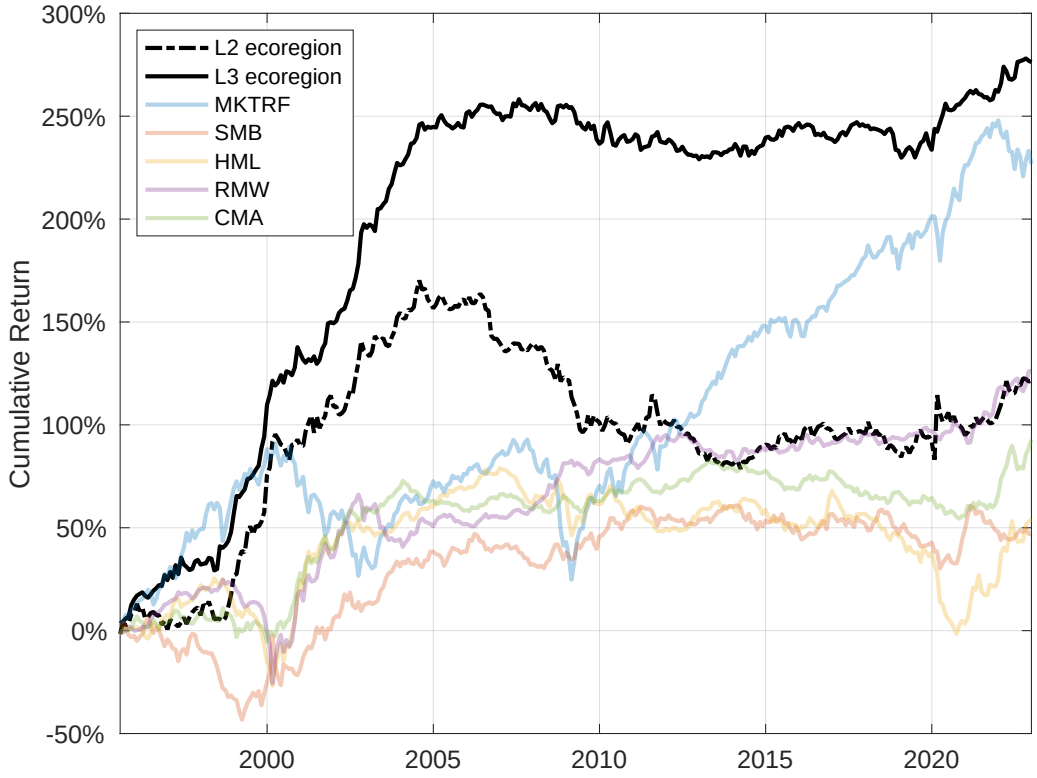


Figure 10: The nature-based trading strategy and momentum. This figure plots the cumulative excess return of the momentum-based ecoregion trading strategy and the momentum factor. Each month, ecoregions are sorted into quintiles based on their equal-weighted return. The strategy is long stocks in the highest momentum ecoregion and short stocks in the lowest momentum ecoregion and the holding period is 1 month. UMD is the momentum factor.

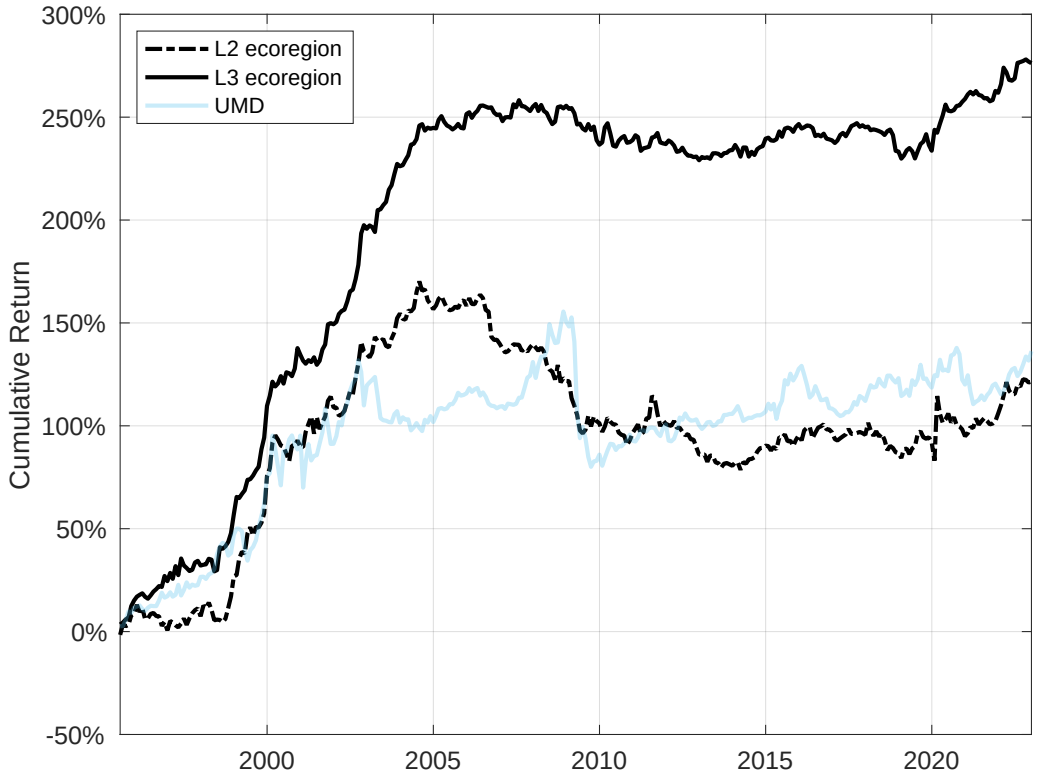


Figure 11: The hurricane track of Hurricane Michael. This figure plots the best track line of Hurricane Michael over the contiguous United States. A 200 mile radius is plotted around the track line. Boundaries indicate level 2 ecoregions.

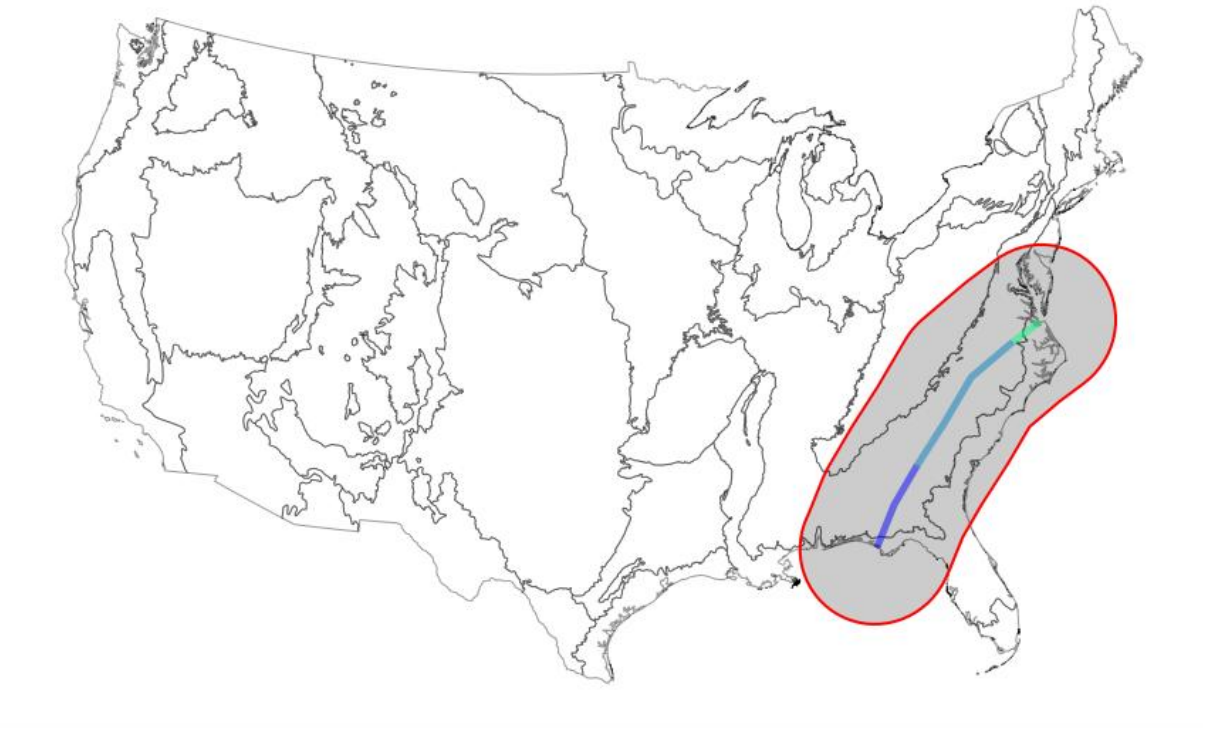


Figure 12: Cumulative returns for stocks within level 2 ecoregions during Hurricane Michael. This figure plots the cumulative mean return for stocks in each level 2 ecoregion that falls within the 200 mile radius of Hurricane Michael. Ecoregions must have at least 6 stocks.

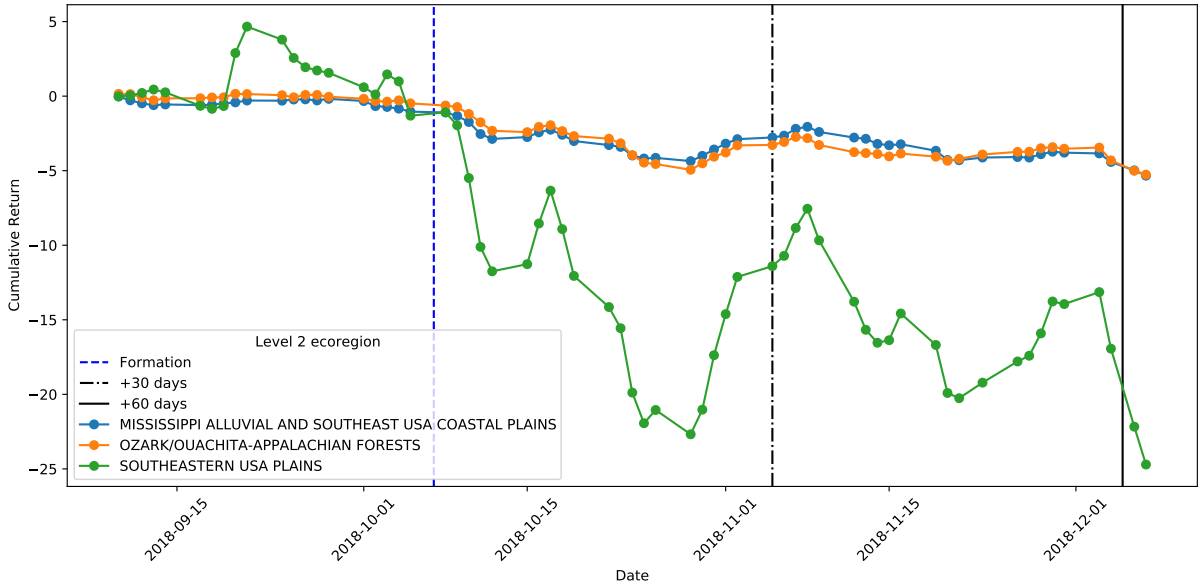


Figure 13: Cumulative returns for stocks within level 3 ecoregions during Hurricane Michael. This figure plots the cumulative mean return for stocks in each level 3 ecoregion that falls within the 200 mile radius of Hurricane Michael. Ecoregions must have at least 6 stocks.

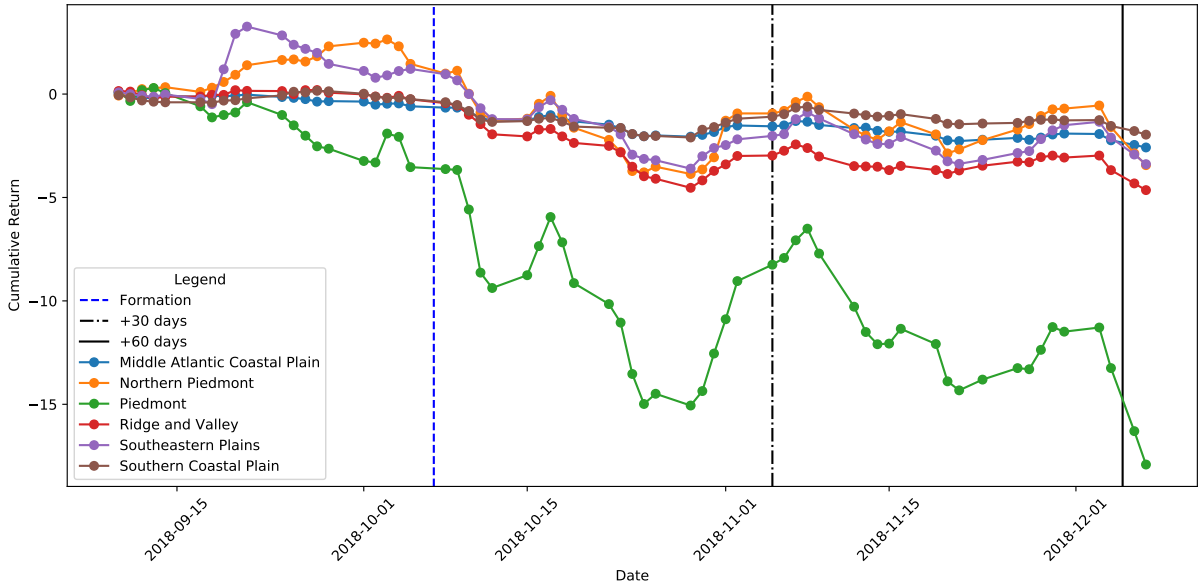


Figure 14: Cumulative returns for stocks within level 4 ecoregions during Hurricane Michael. This figure plots the cumulative mean return for stocks in each level 4 ecoregion that falls within the 200 mile radius of Hurricane Michael. Ecoregions must have at least 6 stocks.

