April 28, 2025

Re: "Natural Capital, Biodiversity, and Corporate Efficiency"

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Natural Capital, Biodiversity, and Corporate Efficiency

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Abstract

Economies have historically developed by depleting biodiversity and other natural capital (Barbier (2011); Jonsson and Wennerlind (2023)). Recent research has established investors' small but growing awareness of biodiversity risk (Garel et al. (2024)). We shine a light on corporate implications of natural capital by computing efficiency for a sample of corporations, and by assessing the link between efficiency, natural capital, and biodiversity. We document that biodiversity does not affect efficiency levels, even in the presence of environmental effects. By contrast, we uncover a strong link between efficiency and natural capital. Moreover, both natural capital and biodiversity contribute to shifting the efficiency frontier.

Keywords: Biodiversity; Natural Capital; Environmental Performance; Corporate Efficiency

JEL Classification: C33; D24; G11; G30; Q51; Q57

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1 Introduction

> We can buy time by reducing population growth and by raising the efficiency parameters ... but no amount of technological progress (A) and produced and human capital formation (K, H) can enable global output Y to grow indefinitely, for sooner or later the biosphere will cross its safety zone at L, and the human economy would in time cease to function. Dasgupta (2024), p.142.

Corporate production uses some resources that are priced and others that are unpriced. Prominent among the unpriced natural resources are biodiversity and other forms of natural capital. Even if regulation does not impose a price on natural resources, governments and corporations may still take environmentally responsible actions in response to potent social norms and public pressure (Araujo et al. (2024)). Such actions can make natural capital show up in measures of technological efficiency. Throughout a long span of economic history, the notion of which resources are scarce and hence connected to technological efficiency has undergone tremendous shifts—from the idea that technology permits sustained, indefinite growth to the opposite idea of capitalism approaching planetary boundaries, beyond which humanity will find it difficult to inhabit Earth in the same way it has in the last ten thousand years (Barbier (2011); Jonsson and Wennerlind (2023)). Recent initiatives to highlight biodiversity by academics and global policymakers represent a key step towards raising public awareness. An important question concerns whether firms are starting to include natural capital in general and biodiversity in particular in their decisions, thereby affecting efficiency. Such management of environmental risk would benefit firms in other respects such as lowering their total cost of capital (Barbier and Burgess (2018)). We document that while natural capital affects the level of efficiency, biodiversity does not. Thus, regulation or increased public awareness must be forthcoming before biodiversity is reflected in firms' efficiency levels.

We focus on the following question: Do biodiversity and other natural capital influence corporate efficiency? Despite the relevance of this topic few studies have addressed it, perhaps due to the paucity of firm-level measures of natural capital and biodiversity. With the advent of databases for such measures, we are able to address the question. A reasonable response is that if biodiversity and natural capital are unpriced, they should have no relation to efficiency. But recent research (Giglio et al. (2023); Garel et al. (2024)) suggests that market participants are starting to pay attention to biodiversity, which may therefore plausibly affect the technology frontiers.[1] Attention is compounded by social pressure from environmental advocates and from global policymakers such as the United Nations. By assessing

[1]For a discussion of the relation of biodiversity and natural capital to business activity see Dasgupta (2024) Chapters 4 and 4*. Efficiency is also related to total factor productivity (TFP), as studied by Hsieh and Klenow (2009) and Whited and Zhao (2021).

the impact of natural capital on efficiency, we shall understand the extent to which corporate performance reflects principal nonmarket factors—and whether policy intervention is required. This is an important undertaking because it illuminates an oft-neglected cost to corporations, a cost that amplifies other environmental externalities. At the outset of this project we were skeptical about finding an efficiency impact, since considerations of natural capital and biodiversity are relatively new in the investor and firm consciousness. Our skepticism was borne out in the case of biodiversity, a subset of natural capital. Nevertheless, we were surprised to uncover significant results for natural capital in general.

Our results complement the prescient research of Barbier and Burgess (2018), who develop a model of firms' investment decisions in the face of environmental risk. The authors demonstrate the benefits of environmental risk management in terms of lowering firms' cost of capital. They highlight the need for national and global polices that coherently inform firms about environmental risks and opportunities: for example, financial regulations that support environmentally sound investment decisions, and mandating coherent reporting standards for environmental risks. Such policies will ensure that environmental considerations such as natural capital and biodiversity are properly considered by firms.

In order to assess the efficiency impact of natural capital and environmental variables, we express them in a stochastic frontier framework. This framework estimates the effect of various factors on business performance, be it physical production, costs, or profits (Kumbhakar and Lovell (2000) Chapter 2). Accordingly, the factors at play can encompass resources such as labour and capital, input costs such as wages, and risk factors such as leverage. We represent natural capital and biodiversity with numerical scores from MSCI. The scores rank companies in terms of environmental resilience—their exposure to key environmental risks, and how well the companies manage such risks. The scores range from 0 to 10, with 0 being the worst performers ("Laggards") and 10 being the best performers ("Leaders"). In order to facilitate effective comparisons across companies—comparing fossil fuel companies to other fossil fuel companies, say, but not to software companies—the scores are based on peers from the same industry.[2] A standard aspect of stochastic frontier estimation involves selecting the performance benchmark. Building on prior business research on efficiency (Nguyen and Swanson (2009) and Chollete et al. (2023)), we specify our benchmark to be corporate profitability, the market value of shareholder equity. We acknowledge that there are other potential benchmarks such as output and Tobin's Q. Nevertheless, the value of shareholder equity is a lodestar in corporate assessment of firm performance, therefore we feel it is a reasonable benchmark.

[2]Further details on score construction are in Chapter 2 of MSCI (2024), and details on our dataset are in Section 4.

There are a number of approaches to measure firm performance. In accounting studies, researchers often use measures such as return on assets, return on equity, and market value added. Finance studies may utilize Tobin's Q, which compares a firm's market value relative to its replacement value of assets. The above methods are useful as swift one-dimensional performance measures. It is important in the present study, however, to control for various firm characteristics, and thereby compare firms to their maximal performance. For example, even if Amazon has the same return on assets as Macy's, Amazon might still have a better performance relative to its own potential. Unlike one-dimensional measures, the stochastic frontier approach is an extension of multivariate regression, and can incorporate diverse variables that explain firm performance. Stochastic frontiers should also be distinguished from complementary efficiency approaches such as data envelopment analysis (Demerjian et al. (2012)). Data envelopment analysis is a highly useful approach to measuring efficiency, in terms of the skill with which each decision making unit converts inputs into outputs. In our context, however, we are interested in how firm efficiency varies over time, when compared to its own potential, as well as in conducting hypothesis testing for natural capital and biodiversity. Moreover, we wish to distinguish bad luck from inefficiency. Such considerations are captured by the frontier approach.

Natural resources may affect efficiency through two channels. The first channel is the effect on average or benchmark efficiency—the location of the frontier. An example of this channel is if individual firms (say, Amazon) use biodiversity-related products like delivery boxes made from protected trees. The second channel occurs when biodiversity risk *shifts* the distance from the frontier or the frontier's distribution, changing all firms' technical capabilities. An example of this channel is if all firms produce or profit less because a biodiversity-dependent medicine for workers is unavailable, making labour underproductive. In order to probe our topic carefully, we shall assess biodiversity risk's impact in both channels.

These two channels by which environmental risk affect a firm's efficiency are distinguished in our paper. Benchmark efficiency (location of the frontier) is captured by adding natural capital and biodiversity as explanatory variables in a regression of firm performance (shareholder equity) on firm debt and other determinants. These are typically called "X" variables. By contrast, variables that can shift the distribution are called "Z" variables, and influence the mean or standard deviation of an inefficiency component u in the regression's error term (Reifschneider and Stevenson (1991); Caudill et al. (1995); Kumbhakar and Lovell (2000) Chapter 7; Habib and Ljungqvist (2005); Chollete et al. (2023)). On the one hand, when we consider natural capital and biodiversity as X variables only natural capital is significant (Tables 2 and 3). On the other hand, when we allow natural capital and biodiversity to shift the frontier as Z variables, they are both significant (Tables 4 and 5). Thus, the

environmental variables—despite being unpriced —do affect market efficiency, especially in shifting the frontier. Note that a positive estimated sign on Z indicates a negative effect on the efficiency distribution. Thus, if we are estimating the effect of Z on the standard deviation σ_u of efficiency, a positive sign means that Z raises the standard deviation of efficiency. Likewise, in estimating the effect of Z on the mean distance μ from the frontier, a positive sign means that Z increases the distance from the frontier, and denotes lower efficiency. Similar to Habib and Ljungqvist (2005), we use idiosyncratic volatility as a Z variable, and supplement it with natural capital and biodiversity.

To fix ideas, we say that corporation i (say, Amazon) is fully efficient if its actual output y_i equals its potential output—that is, its technology frontier $f(r)$, where r denotes resources. We measure efficiency by the ratio $EFF \equiv \frac{y_i}{f(r)}$, and corporate efficiency increases with the value of EFF. Further details on efficiency are in Section 3 and the Appendix. If Amazon uses the factors of natural capital and biodiversity without paying a price, then there is no measurable impact on efficiency. By contrast, if either regulation or public pressure entices Amazon to use inputs from providers that respect natural capital and biodiversity (say, wood from forests that have low risk of endangered species), then Amazon's technological efficiency will reflect natural capital and biodiversity.

2 Literature Review

We join an increasingly germane discussion on financial implications of biodiversity. We build on three research strands. The first strand involves recent studies on biodiversity finance. Karolyi and Tobin-de la Puente (2023) summarise issues in biodiversity finance, distinguish it from climate finance, and call for further research.[3] Flammer et al. (2023) address the issue of financing biodiversity conservation. Using proprietary data on biodiversity-related deals, they find that smaller projects with high expected returns are often financed by private capital, while larger projects often mix private and public capital. Giglio et al. (2023) undertake a systematic assessment of firm exposure to biodiversity risk, based on textual analysis and surveys. They document substantial variation in industry-level biodiversity risk, and provide some evidence that biodiversity risk is related to stock prices. Flammer et al. (2024) study the sustainability implications of blended finance, where public and philanthropic funding are used to encourage private capital. The authors underscore the importance of concessionality, the extent to which the blended investment subsidises the venture. They discover a positive relationship between projects' concessionality and several key vari-

[3]For surveys of the closely related corporate social responsibility literature, see Gillan et al. (2021), and Starks (2023). For a natural resources perspective on biodiversity, see Barbier (2022), chapter 5.

ables, including the projects' sustainability impact, political risk, and information asymmetry. Garel et al. (2024) analyse the corporate biodiversity footprint (CBF), which measures the firm-level impact of biodiversity. The authors document mixed evidence: while CBF does not explain the cross-section of returns in their sample, they discern the emergence of a premium in the wake of important 2021 biodiversity announcements—the establishment up of the Taskforce on Nature-related Financial Disclosures, and the Kunming Declaration. We shall contribute to this important literature by analysing the implications of biodiversity risk for corporate efficiency.

The second strand concerns the ways in which environmental policy can be encouraged by norms and public pressure. A natural contention is that biodiversity disclosure should not matter for market-based firms in the absence of regulation. Without regulation, firms do not internalize biodiversity and therefore we should not expect any effect. By contrast, recent natural resources literature emphasizes non-regulatory avenues both to impel policy action and to actuate firms' environmentally conscious decisions in the absence of regulation. In particular, norms and public pressure can impel governments and firms to foster environmental protection.[4] Araujo et al. (2024) illustrate the power of media and public attention to reduce environmental damage. They focus on the annual forest fires in the Amazon, which went viral in August 2019. Preserving the Amazon's forests is an important goal under the Paris Agreement and the United Nations Sustainable Development Goals. The authors utilize a difference-in-differences approach to compare fires in Brazil, Peru, and Bolivia. They show that increased public attention reduced fires by 22% and avoided nearly 25 million tons of CO2 emissions. This finding is striking because the Brazilian administration was openly opposed to conservation, but still acted because of the surge in public attention. Kruse et al. (2024) study whether markets respond to firms' climate actions. They use the Paris Agreement as a quasi-natural experiment, and document a 10% average increase in cumulative abnormal returns for firms that earn large revenues from green goods and services. The authors conclude that financial markets respond well to the creation of new environmental markets. Zhang and Khanna (2024) study how public pressure can affect firms who do not participate in voluntary environmentally-friendly activities. They show that voluntary activities are more effective when there are high costs to being publicly scrutinized, which lowers the amount of free riders and improves environmental quality. Their model also explains empirical results for voluntary pollution abatement programs.

Social norms also play an outsize role in environmental behavior. An environmental policy may appear inefficient when considering individual firms, but can become efficient if one

[4]For instances of public pronouncements on biodiversity, see the UN statements at https://www.un.org/en/climatechange/science/climate-issues/biodiversity and the listing of biodiversity preservation as UN Sustainable Development Goal 15: https://sdgs.un.org/goals/goal15.

firm's choice to be environmentally aware influences others to do likewise. Dannenberg et al. (2024) emphasize the importance of social norms in environmental behavior. The authors conclude that influencing norms is a powerful tool for environmental policymakers. In related work, Del Campo et al. (2024) evaluate recent research on inequality aversion and climate policy. In particular, they treat the perspective that if society is willing to forego economic efficiency to achieve more equality, that should be incorporated into economic analysis. The authors argue that this perspective is not only academic but used in environmental policy applications and in computing the social cost of carbon. They indicate that it is necessary to allow inequality aversion to vary in policy assessment to account for the possibility of differing stances towards inequality—for example in developed countries versus less developed countries, or foreign aid to reduce global inequality versus national inequality. We add to this literature by providing another setting in which behavioral attitudes to environmental outcomes are important for policymakers and market participants to consider.

The third strand pertains to estimation of efficiency using stochastic frontier analysis. Our approach is related to earlier work by Habib and Ljungqvist (2005), who study the determinants of corporate efficiency in a sample of US firms. Nguyen and Swanson (2009) employ the same methods of efficiency estimation to compare the performance of firms in different efficiency portfolios. Hanousek et al. (2015) analyse efficiency determinants for a sample of European firms. Other examples of the application of efficiency analysis in corporate finance include the estimation of efficiency in the financial sector Berger and Humphrey (1997), insurance (Fenn et al. (2008)), banking (Feng and Zhang (2014)), and privately held firms ahead of their IPOs (Hunt-McCool et al. (1996)). Pereira da Silva (2023) studies the relation between firms' environmental performance and their efficiency. The author documents a positive relation between environmental performance and efficiency. Chollete et al. (2023) compute corporate efficiency for a large group of US firms from 1963 to 2017. They discover large variation in aggregate efficiency over the business cycle, with notable shortfalls during the end of the DotCom bubble, the oil crisis, and the Great Recession. We shall build on these papers by applying a superior panel data estimator based on Kumbhakar et al. (2014), which enables us to separate permanent and transitory inefficiency terms from firm effects. We shall also extend the literature by focusing on the impact of biodiversity risk on efficiency, both alone and in concert with other environmental risks.

3 Methodology

Our concern is whether natural capital and biodiversity affect technical efficiency at the firm level. Our main question is: "Do natural capital and biodiversity influence corporate

efficiency?" In addressing the question we shall compute efficiency for a broad sample of firms, allowing natural capital and biodiversity to change the distance of each firm to its technological frontier.

We use a stochastic frontier approach to analyse how natural capital and biodiversity affect efficiency. Stochastic frontiers extend regression analysis to include a one-sided term to capture efficiency shortfalls. We shall compute the efficiency term in a linear model that regresses firm profitability on firm-level controls and the MSCI measures of Biodiversity land use and Natural Capital, respectively. Section 3.1 provides detail on the econometric model. Readers keen to reach the application can skip to section 3.2.

3.1 The stochastic production frontier model

An essential ingredient of our proposal is technical efficiency. For the past forty years a standard approach to estimating efficiency has used stochastic production frontier (SPF) models (see Aigner et al. (1977) and Kumbhakar and Lovell (2000), among others.) SPF models allow the maximum possible level of output—the frontier—to vary with random firm-specific shocks. A multiplicative random shock ε_i yields an SPF model

$$y_i = f(x_i;\beta)\cdot\exp\{\varepsilon_i\}\cdot A_i. \tag{1}$$

The SPF is given by $f(x_i;\beta)\cdot\exp\{\varepsilon_i\}$ and consists of two parts: a deterministic part $f(x_i;\beta)$ common to all firms and a firm-specific part $\exp\{\varepsilon_i\}$ that captures the impact of random shocks on individual firms. With the stochastic production frontier, the firm efficiency is given by the ratio

$$A_i = \frac{y_i}{f(x_i;\beta)\cdot\exp\{\varepsilon_i\}}. \tag{2}$$

This ratio expresses the observed output generated by the firm relative to its maximum feasible level in a stochastic environment, with stochasticity characterized by $\exp\{\varepsilon_i\}$.

Suppose we have a panel of firms indexed as $i = 1\ldots N$, observed across time periods $t = 1\ldots T_i$, with available data on the relevant inputs and produced quantities. For a Cobb-Douglas production function involving J inputs, log-linearization of Eq. (1) and incorporation of the time dimension yields the panel data stochastic frontier model,

$$\ln y_{it} = \beta_0 + \sum_{j=1}^{J}\beta_j \ln x_{ijt} + \varepsilon_{it}. \tag{3}$$

To estimate firm efficiency in this model, we follow the development by Kumbhakar et al. (2014).[5] We dissect the error term ε_{it} into four distinct and identifiable components as follows:

$$\varepsilon_{it} = \theta_i + v_{it} - \eta_i - u_{it}. \tag{4}$$

The first two components account for time-invariant firm heterogeneity and noise: θ_i is a firm-specific effect that is not related to its efficiency, and v_{it} is a standard random error. The remaining two components are associated with firm efficiency: $\eta_i \geq 0$ embodies persistent inefficiency, while the final term $u_{it} \geq 0$ captures short-term variability in inefficiency. Notice that, unlike firm effects and noise, the two inefficiency terms are asymmetric in relation to zero. This property enables us to estimate the model under appropriate distributional assumptions about the error term and its individual components.

We assume that the four error components are independent and adhere to the following distributions. The two-sided components are normally distributed, $\theta_i \sim N\left(0, \sigma_\theta^2\right)$ and $v_{it} \sim N\left(0, \sigma_v^2\right)$. The error components associated with inefficiency have truncated normal distributions. They are heteroskedastic, and their variances are allowed to vary systematically across firms: $\eta_i \sim N^+\left(\mu_\eta, \sigma_{\eta i}^2\right)$ and $u_{it} \sim N^+\left(\mu_u, \sigma_{ui}^2\right)$.[6] We parameterize heteroskedasticity as a linear function of observable firm characteristics z_i. Intuitively, firms expect to experience different variability in their inefficiencies conditional on observables z_i, such as firm size or production inputs. To ensure that the estimated variance parameters are positive, we follow Caudill et al. (1995) and adopt the parametrization $\sigma_{\eta i}^2 = \exp\left(z'_{\gamma i}\gamma_\eta\right)$ and $\sigma_{ui}^2 = \exp\left(z'_{ui}\gamma_u\right)$.

We estimate the model in three stages. First, we use a standard fixed effects estimator[7] to obtain residuals $\hat{e}_{it}$ and firm-specific effects $\hat{\mu}_i$ from the model

$$\ln y_{it} = \beta_0^* + \sum_{j=1}^{J} \beta_j \ln x_{ijt} + \mu_i + e_{it}, \tag{5}$$

where we define the intercept $\beta_0^* = \beta_0 - \mathrm{E}(\eta_i) - \mathrm{E}(u_{it})$, fixed effects $\mu_i = \theta_i - \eta_i + \mathrm{E}(\eta_i)$ and errors $e_{it} = v_{it} - u_{it} + \mathrm{E}(u_{it})$. Second, we use model residuals from the first stage, $\hat{e}_{it}$, to obtain Jondrow et al. (1982) maximum likelihood estimator of time-varying inefficiency u_{it}. Similarly, in the third step we estimate persistent inefficiency η_i from information contained in the fixed effects $\hat{\mu}_i$. We construct overall corporate efficiency estimates as the product of point estimates for time-varying and persistent efficiencies, $EFF_{it} = \exp(-\hat{u}_{it} - \hat{\eta}_i)$.

[5] This strategy extends work by Greene (2005a) and Greene (2005b) on 'true' fixed and random effects, which disentangle heterogeneity from persistent firm-specific inefficiency in panel SPF models.

[6] The notation $N^+(\mu, \sigma^2)$ means upper truncation of a normal distribution $N(\mu, \sigma^2)$ at 0.

[7] Kumbhakar et al. (2014) use the random effects estimator. We prefer the fixed effects estimator because its consistency does not depend on the strict mean independence assumption, $\mathrm{E}(\mu_i | x_{ij}) = 0$, which we think is unlikely to hold in our data.

3.2 Empirical specification of technological efficiency

We specify the dependent and explanatory variables that characterize firm output and inputs in the estimated equation (5) based on previous empirical research. The dependent variable is the log of market value of shareholder equity. Maximizing the value of shareholder equity is a core firm objective in corporate finance that sets a benchmark for evaluating the firm's performance and its long-term potential. In choosing the equity component of firm value as an output indicator, we follow Nguyen and Swanson (2009) and Chollete et al. (2023). An alternative measure could be Tobin's Q, as used by Habib and Ljungqvist (2005).

We recognize that there are options for approaching efficiency estimation. Some researchers applying the stochastic frontier methodology focus on factors of production: labour, capital, and so forth (Gaynor and Pauly (1990), Kumbhakar et al. (2014)). Other researchers use a finance based model that relates efficiency to standard variables from corporate finance—firm size, advertising, and so on (Habib and Ljungqvist (2005), Nguyen and Swanson (2009)). Since we are interested in corporate profitability, we use some elements of the finance approach, such as market value for the target variable. We also incorporate economic variables such as labour and capital proxies, both for intuitive appeal and because those variables better satisfy diagnostic tests. A basic econometric requirement for the stochastic frontier models is that their residuals be negatively skewed (see Kumbhakar and Lovell (2000), p. 73). However, a model with only financial variables as controls does not pass the skewness test. Results from this specification are available from the authors upon request.

Building upon prior research (Nguyen and Swanson (2009) and Habib and Ljungqvist (2005)), we incorporate several additional controls. Our objective is to establish a benchmark for the market value of a firm's equity, leading our selection of explanatory variables that are informative of future cash flows and discount rates. We account for growth opportunities and forward-looking behavior by using the firm's capital expenditures as a measure of investment in tangible assets. Additionally, expenses on R&D and advertising serve as controls for investment in intangible assets. These three variables signify management's commitment to firm growth and openness to investment opportunities. We anticipate them to have a positive relationship with the firm's market value when management and shareholder interests are well-aligned. Beyond these variables we also consider stock return volatility, which varies interestingly for firms with differential exposure to environmental risk (Chollete et al. (2024)). We therefore allow return volatility to affect the frontier, as in Habib and Ljungqvist (2005). We use the net value of property, plant and equipment as a measure of the firm's capital

stock. Labour input is measured by the number of employees.[8] To capture biodiversity and natural capital, we use the biodiversity-land use and natural capital scores from MSCI. And to capture environmental risk, we use a comprehensive environmental score from MSCI.

The ratio of long-term debt to total assets addresses leverage considerations. Leverage, when used appropriately, can enhance expected firm value, yet it may also exhibit a negative correlation with the market value of equity during market downturns. Finally, we capture unobservable differences between super star firms and the rest of the market by introducing a dummy variable that takes on a value of one if the firm falls into the top five percent based on the market cap criterion in a given fiscal year, and zero otherwise.

The Compustat advertising and R&D variables contain a substantial number of missing values. To prevent discarding potentially valuable information, we opt for imputing missing data. Since all available imputation methods have their advantages and limitations (see the discussion in Little and Rubin (2019)), we rely on our understanding of the mechanism causing missingness to choose the most suitable approach. In many corporate situations, advertising and R&D expenses are unreported because their true amounts are negligible (p.364 Himmelberg et al. (1999)). We therefore employ a simple zero imputation method, replacing missing values with zeros and introducing a dummy variable that equals one if the value is missing and zero otherwise. Although using zeros as substitutes for missing values is generally inappropriate, in the present context it offers the benefits of simplicity, retaining all observations, not relying on an unverifiable probability model, and appearing to satisfy the mechanism behind much of the missingness.

4 Data Description and Empirical Tests

We utilize data from several sources. We collect environmental performance and climate risk information from MSCI's ESG database. MSCI contains the ESG scores based on three pillar ratings: environmental pillar, social pillar, and governance pillar. The pillars provide ratings on firms' resilience to financially material environmental, societal, and governance conditions. In addition, MSCI contains measures of natural capital and biodiversity land use. MSCI covers global firms from 2007 to the present. We use industry-adjusted weighted average scores of the three pillars. We also use the environmental pillar score, carbon emission, and climate change theme scores for robustness tests. These latter data are available from 2013 to 2023.

[8] Labour expenses are available in Compustat, but contain a large number of missing values. We therefore use the number of employees to measure the labour input.

We collect information on firm characteristics from COMPUSTAT North America, which contains publicly listed company data from 1950 to 2023. We collect stock returns data from CRSP, which contains stock data for over 32,000 securities with primary listings on the NYSE, NYSE American, NASDAQ, NYSE Arca, and Cboe BZX exchanges. Stock price data are available for NYSE firms from 1925 to 2023. For NASDAQ firms data are available from 1962 to 2023.

We propose two hypotheses for the efficiency impact of natural capital and biodiversity, reflecting our discussion in the Introduction. Hypothesis 1 says that firms with higher biodiversity scores have lower efficiency, since biodiversity is at present still unpriced in unregulated markets. Hypothesis 2 says that firms with higher natural capital scores have lower efficiency, since it is still financially costly to maintain natural capital.

Hypothesis 1: *Biodiversity is Negatively related to technological efficiency*

Hypothesis 2: *Natural Capital is Negatively related to technological efficiency*

5 Results

We constructed our dataset from the sources described above. Given that we conduct two sets of estimations with different variables, we provide summary statistics for both sets, in Panels A and B of Table 1. There is not much difference between the two datasets. Market value of equity is by far the largest single variable, while idiosyncratic volatility is the smallest. The average natural capital and environmental scores are considerably larger than the biodiversity scores. We find a substantial degree of variation in our data, as evidenced by the standard deviations. This variation indicates that statistical analysis may be fruitful.

Table 2 presents our results from estimating the efficiency model using both natural capital and environmental scores as determinants of efficiency. Both of these variables and their interaction turn out to be significant. We divide the table into three panels corresponding to the steps of the estimation procedure. The top panel reports fixed effects estimates of Eq.(5). To validate the specification, we examine the first-step residuals $\hat{e}_{it}$ and estimated fixed effects $\hat{\mu}_i$. For the error ε_{it} in Eq. (3) to be consistent with one-sided error components η_i and u_{it}, both $\hat{e}_{it}$ and $\hat{\mu}_i$ must have left-skewed distributions. The estimated coefficients of skewness are negative, $\text{Sk}(\hat{e}) = -0.125$ and $\text{Sk}(\hat{\mu}) = -0.218$. In both cases, the null hypothesis of no skewness is rejected with p-values below 0.001. Since the model is consistent with the technology specification, we can estimate transitory and permanent efficiency. The lower two panels present maximum likelihood estimates of permanent and transitory efficiency com-

ponents. For each component, we test the null hypothesis of technical efficiency. If all firms were operating at the frontier, inefficiency would be irrelevant: we would have $\mu_u = \sigma^2_{ui} = 0$ for transitory inefficiency, and $\mu_\eta = \sigma^2_{\eta i} = 0$ for permanent inefficiency. The likelihood ratio test in both instances rejects the null hypothesis of technical efficiency with a p-value below 0.001, supporting our model specification. We combine the inefficiency components to compute overall efficiency for each firm-year. The main takeaway from this Table is that both natural capital and environmental performance affect efficiency. The interaction term has a negative coefficient, suggesting a synergistic effect from the two factors: the occurrence of both large natural capital and large environmental scores may lead to higher efficiency, while the opposite is true when only considering one factor at a time.

Table 3 is similar to the preceding Table, with biodiversity replacing natural capital as the main variable. The model selection result is mixed: the skewness test is significant for the $\hat{\mu}$ but not for $\hat{e}$. Nevertheless, the diagnostic likelihood ratio test rejects the hypothesis of technical efficiency. Thus, to the extent that this specification is reliable, there is evidence of inefficiency. The fragility of using biodiversity is borne out by its insignificance in step 1: for this specification biodiversity is not significant, whether singly or in concert with the environmental score. Our main takeaway therefore, is that biodiversity does not appear to influence corporate efficiency levels, while natural capital does. Our results merit followup, for example, by analyzing extensions in future research.

One important extension is the potential for natural capital to shift the frontier itself. Thus far, we have emphasized the measurement of efficiency as distance from the frontier. As we mentioned in the Introduction, another important avenue for natural capital to affect efficiency concerns shifting the frontier. We therefore provide further results where we allow for natural capital or biodiversity to shift the distribution of efficiency. We explored eight models that involved natural capital and biodiversity singly, in concert, and with environmental and interaction terms. Two models did not converge. The models that did converge all passed the skewness test for the model specification. Of those models we focus on the most parsimonious ones, which only add one variable—natural capital or biodiversity—to the previous specifications for transitory and persistent efficiency.

Table 4 shows estimated results from a stochastic frontier model using natural capital as a potential driver of the frontier. We focus on panels 2 and 3 in the Table, which examine the impact of natural capital on transitory and persistent efficiency, respectively. The estimated skewness is negative, and the null hypothesis of no skewness in the residuals is rejected with a p-value of 0.000, indicating that the model is consistent with the technology specification. In Panel 2, we see that natural capital does not matter for transitory efficiency, while Panel 3 indicates that natural capital is highly significant for persistent efficiency. Table 5 is similar

to the preceding Table, but with biodiversity replacing natural capital. The results are similar: biodiversity is marginally insignificant for transitory efficiency, and strongly significant for persistent efficiency. Thus, this Table and the previous one show that both natural capital and environmental performance have strong persistent effects for the efficiency frontier.

Figure 2 presents a kernel density plot depicting the distribution of estimated efficiency scores, based on the frontier estimates in Table 4. The distribution is skewed to the left, revealing a notable gap between top-performing companies and those with lower efficiency. While most firms exhibit efficiency within one standard deviation of the sample mean, the left tail extends to a minimal efficiency level of below 3%. For illustration, we highlight several observations from the 2018 subsample of retail firms. The results are intuitive: retail giants like Home Depot and Walmart operate with above-average efficiency, while less prominent retailers populate the left tail of the distribution.

6 Conclusions

Economic development often entails increased production by corporations, which deplete unpriced natural resources such as biodiversity in pursuit of technological efficiency (Barbier (2011); Jonsson and Wennerlind (2023)). We study how biodiversity and natural capital affect technological efficiency. This is an important undertaking because it illuminates an oft-neglected aspect of corporate production, an aspect that amplifies other environmental externalities. Our paper shines light on the nexus between firms and natural resources by computing efficiency for a broad sample of firms, and by assessing the relation between efficiency, natural capital, and biodiversity.

Biodiversity sometimes goes hand in hand with environmental factors such as climate risk, but at other times diverges. We therefore include a separate environmental score, and allow for its interaction with biodiversity and natural capital. We document that biodiversity does not affect corporate efficiency levels, even in the presence of environmental factors. By contrast, a broad measure of natural capital does indeed influence technological efficiency of firms. Despite being unpriced factors, both natural capital and biodiversity have significant effects in shifting the efficiency frontier. It is in society's interest to ensure that such environmental impacts on business are accounted for, which will require broader awareness of natural resource effects, as well as concomitant public policies. Our perspective and empirical results mirror theoretical work such as Barbier and Burgess (2018), which highlights the importance of public policies that support effective management of environmental risks.

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A Background on Stochastic Frontier Models

Suppose we have a sample of I firms, with cross-sectional data on inputs employed, quantity produced, and total expenditures. A deterministic production frontier model can be written

$$y_i = f(x_i;\beta)\cdot PE_i, \quad i = 1,...,I, \tag{6}$$

where y_i is the output of firm i, x_i is a vector of inputs for firm i, $f(x_i;\beta)$ is the production frontier common to all firms, and β is a vector of technology parameters to be estimated. PE_i is the productive or technical efficiency of firm i.[9] We write the productive efficiency of a firm as PE_i, which from (6) is

$$PE_i = \frac{y_i}{f(x_i;\beta)}. \tag{7}$$

The above expression defines productive efficiency as the ratio of observed output to the maximum feasible output. A necessary and sufficient condition for y_i to achieve its maximum value of $f(x_i;\beta)$ is that $PE_i = 1$. Otherwise $PE_i < 1$ measures the shortfall of observed production from the frontier. In equation (7) the entire shortfall of PE_i from the frontier $f(x_i;\beta)$ is attributed to inefficiency. In order to incorporate firm-specific random shocks into the analysis, we need to specify a stochastic production frontier. Therefore we can rewrite equation (6) as

$$y_i = f(x_i;\beta)\cdot \exp\{v_i\}\cdot PE_i, \tag{8}$$

where $[f(x_i;\beta)\cdot \exp\{v_i\}]$ is the stochastic production frontier (SPF). The SPF comprises two parts: a deterministic part $f(x_i;\beta)$ common to all firms, and a firm-specific part $\exp\{v_i\}$, which captures the effect of random shocks on each company. If the production frontier is specified as being stochastic, the expression for efficiency from equation (7) now becomes

$$PE_i = \frac{y_i}{f(x_i;\beta)\cdot \exp\{v_i\}}. \tag{9}$$

[9] Technical efficiency denotes a firm's ability to minimize input to produce a given output, or maximize output for a given input. See Kumbhakar and Lovell (2000), chapter 2.

The reformulation in expression (9) defines efficiency as the ratio of observed output to maximum feasible output, in a stochastic environment, which is characterized by $\exp\{v_i\}$.

Graphical Intuition. Consider an hypothetical graph of Macy's and Amazon, as in Figure 1. For given inputs x, the firms produce some output y. However, the firms may have different productive potentials, therefore it is important to compare them relative to their '*best selves*'. For example, if Amazon's maximal output value is double that of Macy's, a raw comparison of the companies' output will not convey how successful they are at reaching their potential. The efficiency approach compares each company to the best output it could achieve, via the size of the efficiency terms u_1 and u_2.

Figure 1: **Hypothetical Production Frontier**

The figure shows an hypothetical illustration of the production frontier. u_1 and u_2 represent the inefficiency effects from the two different companies.

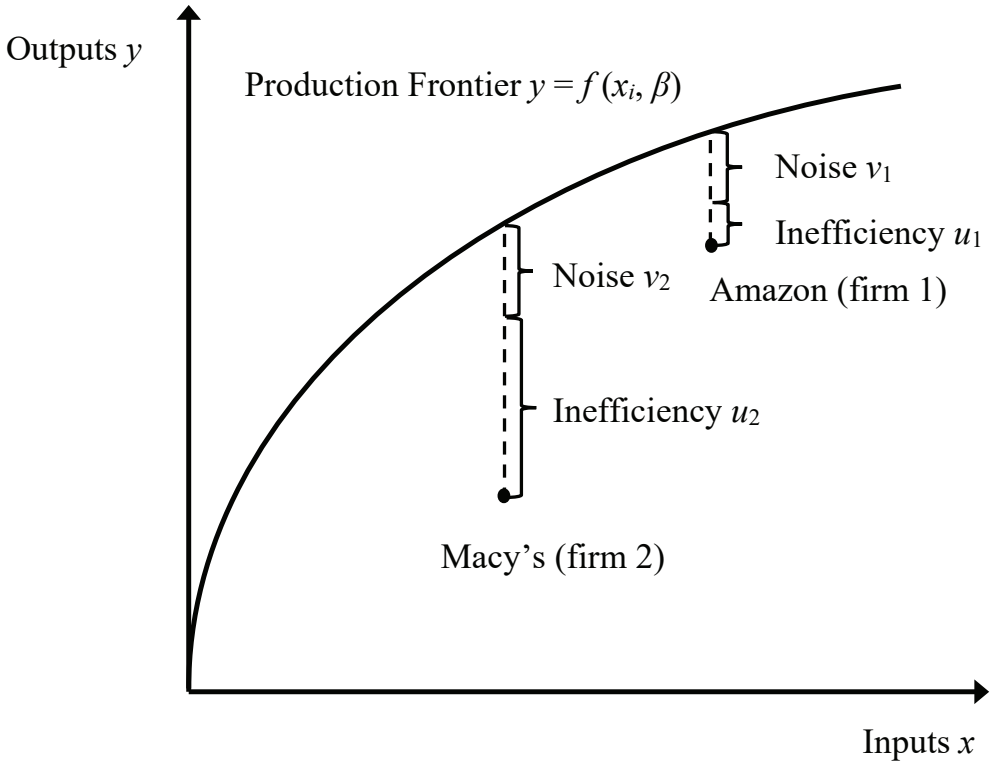


Table 1: **Summary Statistics of Variables for stochastic frontier analysis**

The table presents summary statistics of the variables used in the stochastic frontier analysis. Daily stock returns are retrieved from CRSP. Environmental scores, Biodiversity, and Natural capital theme scores are from MSCI. All other data are from COMPUSTAT. The sample comprises nonfinancial nonutility firms from fiscal year 2013 to 2020.

Panel A: Variables for Model with Natural Capital

Variable	Obs	Mean	Std. Dev.	Min	Max
Market value of equity, log	3,880	15.5784	1.5596	11.7874	21.0676
Net value of property, plant and equipment, log	3,880	7.4197	1.9136	-0.0578	12.8395
Employment in thousands, log	3,880	2.2655	1.6050	-3.9120	7.7407
Capital expenditures, log	3,880	5.5615	1.8603	-0.0880	11.2554
R&D expenses, log	3,880	2.2957	2.9424	-0.0880	10.6300
Indicator for missing R&D data	3,880	0.5735	0.4946	0	1
Advertising expenses, log	3,880	2.3760	2.7986	-0.0880	9.8933
Indicator for missing advertising data	3,880	0.5137	0.4999	0	1
Long-term debt to assets ratio	3,880	0.2395	0.2052	0	2.3610
Firm in the top 5% by market cap	3,880	0.1204	0.3254	0	1
Natural Capital Theme Score	3,880	4.2309	2.4715	0	10
Environmental Pillar Score	3,880	4.5938	2.1939	0	10
Natural Cap. Theme Score × Environ. Score	3,880	21.8276	19.3819	0	100
Idiosyncratic volatility, daily stock returns	3,880	0.0157	0.0077	0.0048	0.0811

Panel B: Variables for Model with Biodiversity & Land Use

Variable	Obs	Mean	Std. Dev.	Min	Max
Market value of equity, log	3,035	15.2985	1.5017	11.6403	21.0676
Net value of property, plant & equipment, log	3,035	7.1813	1.9331	-0.0578	12.8395
Employment in thousands, log	3,035	1.9508	1.5812	-3.9120	7.7407
Capital expenditures, log	3,035	5.2170	1.9280	-0.0880	11.2554
R&D expenses, log	3,035	2.1327	2.7711	-0.0880	10.6300
Indicator for missing R&D data	3,035	0.5295	0.4992	0	1
Advertising expenses, log	3,035	1.9076	2.5498	-0.0880	9.5299
Indicator for missing advertising data	3,035	0.4738	0.4994	0	1
Long-term debt to assets ratio	3,035	0.2503	0.2123	0	2.3610
Firm in the top 5% by market cap	3,035	0.0939	0.2917	0	1
Biodiversity & Land Use Score	3,035	2.9944	2.1270	0	10
Environmental Pillar Score	3,035	4.5348	2.1971	0	10
Biodiv. Land Use Score × Environ. Score	3,035	12.8467	9.3229	0	59.8400
Idiosyncratic volatility, daily stock returns	3,035	0.0183	0.0093	0.0048	0.0939

Table 2: **Natural Capital and Corporate Efficiency**

The table presents estimates of the stochastic frontier model described by Eq. (3)-(4). The estimates are computed in three steps using the procedure of Kumbhakar et al. (2014). The dependent variable in Step 1 is the market value of shareholder's equity. Standard errors are clustered at the firm level in the first step. The variances of inefficiency error components u and η vary with idiosyncratic volatility. The number of observations is 3,880. The sample comprises nonfinancial, nonutility Compustat firms from 2001 to 2020, as in Table 1.

Variable	Estimate	S.E.	p-value
Step 1. Fixed effects estimates of Eq. (5)			
Net value of property, plant and equipment, log	0.160	0.041	0.000
Employment in thousands, log	0.292	0.078	0.000
Capital expenditures, log	0.100	0.026	0.000
R&D expenses, log	0.005	0.055	0.922
Indicator for missing R&D data	-0.110	0.187	0.554
Advertising expenses, log	0.007	0.025	0.794
Indicator for missing advertising data	-0.025	0.094	0.791
Long-term debt to assets ratio	-0.236	0.194	0.224
Firm in the top 5% by market cap	0.486	0.040	0.000
Natural Capital Theme Score	0.019	0.008	0.019
Environmental Pillar Score	0.031	0.011	0.006
Natural Cap. Theme Score × Environ. Score	-0.003	0.001	0.024
Constant	13.069	0.313	0.000
R-squared	0.218		
Skewness in the fixed effects $\hat{\mu}_i$	-0.218		0.000
Skewness in the residuals $\hat{e}_{it}$	-0.125		0.002
Step 2. ML estimates of transitory inefficiency u_{it}			
Frontier	0.110	0.009	0.000
Transitory mean, μ_u	-28.597	131.478	0.828
Transitory variance, γ_u:			
Idiosyncratic volatility	45.866	5.054	0.000
Constant	0.356	4.595	0.938
Variance of the error term, $\log\sigma_v^2$	-2.894	0.034	0.000
Likelihood ratio test of model significance	156.9		0.000
Likelihood ratio test of $\sigma_u^2 = 0$ and $\mu_u = 0$	271.7		0.000
Step 3. ML estimates of persistent inefficiency η_i			
Frontier	0.671	0.051	0.000
Persistent mean, μ_η	-0.335	0.210	0.111
Persistent variance, γ_η:			
Idiosyncratic volatility	89.561	5.835	0.000
Constant	-1.580	0.209	0.000
Variance of the firm-specific effects, $\log\sigma_\mu^2$	-0.707	0.061	0.000
Likelihood ratio test of model significance	173.6		0.000
Likelihood ratio test of $\sigma_\eta^2 = 0$ and $\mu_\eta = 0$	463.5		0.000

Table 3: **Biodiversity and Corporate Efficiency**

The table presents estimates of the stochastic frontier model described by Eq. (3)-(4). The estimates are computed in three steps using the procedure of Kumbhakar et al. (2014). The dependent variable in Step 1 is the market value of shareholder's equity. Standard errors are clustered at the firm level in the first step. The variances of inefficiency error components u and η vary with idiosyncratic volatility. The number of observations is 3,035. The sample comprises nonfinancial, nonutility Compustat firms from 2001 to 2020, as in Table 1.

Variable	Estimate	S.E.	p-value
Step 1. Fixed effects estimates of Eq. (5)			
Net value of property, plant and equipment, log	0.134	0.034	0.000
Employment in thousands, log	0.353	0.085	0.000
Capital expenditures, log	0.010	0.023	0.672
R&D expenses, log	0.054	0.059	0.362
Indicator for missing R&D data	-0.337	0.217	0.120
Advertising expenses, log	0.012	0.031	0.686
Indicator for missing advertising data	-0.104	0.119	0.385
Long-term debt to assets ratio	-0.781	0.216	0.000
Firm in the top 5% by market cap	0.428	0.057	0.000
Biodiversity & Land Use Score	-0.029	0.021	0.158
Environmental Pillar Score	-0.003	0.019	0.884
Biodiv. Land Use Score × Environ. Score	0.002	0.004	0.566
Constant	13.915	0.288	0.000
R-squared	0.143		
Skewness in the fixed effects $\hat{\mu}_i$	-0.093		0.036
Skewness in the residuals $\hat{e}_{it}$	-0.014		0.759
Step 2. ML estimates of transitory inefficiency u_{it}			
Frontier	0.100	0.008	0.000
Transitory mean, μ_u	-20.468	89.513	0.819
Transitory variance, γ_u:			
Idiosyncratic volatility	41.257	4.771	0.000
Constant	-0.109	4.363	0.980
Variance of the error term, $\log\sigma_v^2$	-3.065	0.035	0.000
Likelihood ratio test of model significance	142.1		0.000
Likelihood ratio test of $\sigma_u^2 = 0$ and $\mu_u = 0$	216.5		0.000
Step 3. ML estimates of persistent inefficiency η_i			
Frontier	0.574	0.055	0.000
Persistent mean, μ_η	-0.384	0.254	0.131
Persistent variance, γ_η:			
Idiosyncratic volatility	79.937	6.325	0.000
Constant	-1.883	0.286	0.000
Variance of the firm-specific effects, $\log\sigma_\mu^2$	-0.393	0.049	0.000
Likelihood ratio test of model significance	109.9		0.000
Likelihood ratio test of $\sigma_\eta^2 = 0$ and $\mu_\eta = 0$	323.2		0.000

Table 4: **Natural Capital and Corporate Efficiency when Natural Capital can Shift the Frontier**

The table presents estimates of the stochastic frontier model described by Eq. (3)-(4). The estimates are computed in three steps using the procedure of Kumbhakar et al. (2014). The dependent variable in Step 1 is the market value of shareholder's equity. Standard errors are clustered at the firm level in the first step. The variances of inefficiency error components u and η vary with idiosyncratic volatility. The number of observations is 5,480. The sample comprises nonfinancial, nonutility Compustat firms from 2001 to 2020, as in Table 1.

Variable	Estimate	S.E.	p-value
Step 1. Fixed effects estimates of Eq. (5)			
Net value of property, plant and equipment, log	0.264	0.027	0.000
Employment in thousands, log	0.348	0.039	0.000
Capital expenditures, log	0.108	0.014	0.000
R&D expenses, log	0.104	0.022	0.000
Indicator for missing R&D data	-0.099	0.088	0.262
Advertising expenses, log	0.000	0.017	0.990
Indicator for missing advertising data	-0.027	0.068	0.694
Long-term debt to assets ratio	-0.718	0.116	0.000
Firm in the top 5% by market cap	0.763	0.048	0.000
Constant	11.751	0.144	0.000
R-squared	0.218		
Skewness in the fixed effects $\hat{\mu}_i$	-0.031		0.044
Skewness in the residuals $\hat{e}_{it}$	-0.422		0.000
Step 2. ML estimates of transitory inefficiency u_{it}			
Frontier	0.346	0.014	0.000
Transitory mean, μ_u	-1.589	0.947	0.093
Transitory variance, γ_u:			
Natural Capital Theme Score	0.016	0.015	0.289
Idiosyncratic volatility	70.889	6.200	0.000
Constant	-2.494	0.561	0.000
Variance of the error term, $\log\sigma_v^2$	-1.947	0.026	0.000
Likelihood ratio test of model significance	655.6		0.000
Likelihood ratio test of $\sigma_u^2 = 0$ and $\mu_u = 0$	35188.799		0.000
Step 3. ML estimates of persistent inefficiency η_i			
Frontier	0.592	0.033	0.000
Persistent mean, μ_η	-0.235	0.139	0.091
Persistent variance, γ_η:			
Natural Capital Theme Score	-0.131	0.020	0.000
Idiosyncratic volatility	72.019	5.368	0.000
Constant	-1.860	0.226	0.000
Variance of the firm-specific effects, $\log\sigma_\mu^2$	-0.643	0.030	0.000
Likelihood ratio test of model significance	327.9		0.000
Likelihood ratio test of $\sigma_\eta^2 = 0$ and $\mu_\eta = 0$	54028.0		0.000

Table 5: **Biodiversity and Corporate Efficiency when Biodiversity can Shift the Frontier**

The table presents estimates of the stochastic frontier model described by Eq. (3)-(4). The estimates are computed in three steps using the procedure of Kumbhakar et al. (2014). The dependent variable in Step 1 is the market value of shareholder's equity. Standard errors are clustered at the firm level in the first step. The variances of inefficiency error components u and η vary with idiosyncratic volatility. The number of observations is 4,687. The sample comprises nonfinancial, nonutility Compustat firms from 2001 to 2020, as in Table 1.

Variable	Estimate	S.E.	p-value
Step 1. Fixed effects estimates of Eq. (5)			
Net value of property, plant and equipment, log	0.264	0.027	0.000
Employment in thousands, log	0.348	0.039	0.000
Capital expenditures, log	0.108	0.014	0.000
R&D expenses, log	0.104	0.022	0.000
Indicator for missing R&D data	-0.099	0.088	0.262
Advertising expenses, log	0.000	0.017	0.990
Indicator for missing advertising data	-0.027	0.068	0.694
Long-term debt to assets ratio	-0.718	0.116	0.000
Firm in the top 5% by market cap	0.763	0.048	0.000
Constant	11.751	0.144	0.000
R-squared	0.314		
Skewness in the fixed effects $\hat{\mu}_i$	-0.031		0.044
Skewness in the residuals $\hat{e}_{it}$	-0.422		0.000
Step 2. ML estimates of transitory inefficiency u_{it}			
Frontier	0.461	0.032	0.000
Transitory mean, μ_u	-0.380	0.427	0.374
Transitory variance, γ_u:			
Biodiversity & Land Use Score	-0.034	0.018	0.066
Idiosyncratic volatility	73.778	7.586	0.000
Constant	-2.987	0.526	0.000
Variance of the error term, $\log\sigma_v^2$	-1.802	0.038	0.000
Likelihood ratio test of model significance	142.1		0.000
Likelihood ratio test of $\sigma_u^2 = 0$ and $\mu_u = 0$	34970.1		0.000
Step 3. ML estimates of persistent inefficiency η_i			
Frontier	0.519	0.034	0.000
Persistent mean, μ_η	-0.239	0.148	0.106
Persistent variance, γ_η:			
Biodiversity & Land Use Score	0.141	0.022	0.000
Idiosyncratic volatility	62.699	5.084	0.000
Constant	-2.921	0.300	0.000
Variance of the firm-specific effects, $\log\sigma_\mu^2$	-0.641	0.030	0.000
Likelihood ratio test of model significance	234.04		0.000
Likelihood ratio test of $\sigma_\eta^2 = 0$ and $\mu_\eta = 0$	55890.1		0.000

Figure 2: **Distribution of the Estimated Corporate Efficiency Scores**

The figure displays kernel density function of the estimated corporate efficiency scores (Epanechnikov kernel, bandwidth $h = 0.01$). Efficiency scores are computed using the estimates from Table 4, and the underlying model is based upon Kumbhakar et al. (2014) as described in Section 2. Highlighted points are selected for illustrative purposes from the subsample of retail firms in 2018.

