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The Impact of Firm Technology on Carbon Disclosure: The Critical Role of Stakeholder Pressure

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Abstract

The demand for transparency about the microeconomic sources of environmental pollution has surged recently, causing carbon disclosure to rise to the top of the global climate change discourse. In this study, we empirically investigate how the environmental performance of firm production technologies shapes their voluntary carbon disclosure behaviour and how key stakeholders influence the performance-disclosure relationship. Using a panel of 1,547 firms across 24 countries covering 2006–20, we find that firms with the most efficient technologies for reducing emissions tend to disclose their carbon impact, especially when they face more stringent environmental regulations. These high-performing firms demonstrate a tendency for non-disclosure when faced with intense shareholder and environmental activist pushback against pollution. Our findings also highlight the existence of a profitability penalty for transparent high-efficiency firms relative to comparable firms that adopt strategic silence.

I. Introduction

Carbon disclosure has become a hot-button issue[1] and an important public policy priority[2] due to the rising global concern about climate change. According to the Carbon Disclosure Project (CDP),[3] around 13,000 companies voluntarily disclosed their carbon emissions in 2021, representing over 140% growth since 2015 (CDP, 2021). Concurrently, improving the energy efficiency of production operations has become a notable corporate social responsibility (CSR) aspiration of many corporations (Laguir *et al.*, 2019). The World Wildlife Fund (WWF, 2017) indicates that around 50% of Fortune 500 have set

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[1] For instance, see https://www.economist.com/special-report/2022/07/21/measure-less-but-better and https://www.ft.com/content/27e3d5f8-2fb4-4b8b-8d94-78dc084ede58.

[2] For example, with effect from 6 April 2022, a recent UK legislation mandates environmental disclosure for its largest companies. See: https://www.gov.uk/government/news/uk-to-enshrine-mandatory-climate-disclosures-for-largest-companies-in-law.

[3] https://www.cdp.net/en.

targets to reduce greenhouse gases (GHG) by improving energy efficiency. However, as firms strategically improve the energy efficiency of their operations, it remains unclear whether/how such improvements influence their voluntary carbon disclosure.

Starting from the wider literature, we note the growing body of research examining the main determinants of environmental disclosures (Duflo *et al.*, 2013; Kim, Ryou, and Yang, 2020), as well as the effects of these disclosures on financial indicators (Servaes and Tamayo, 2013; Krüger, 2015) and environmental performance (Wang *et al.*, 2019). Additionally, previous studies have also explored firms' strategic use of environmental disclosures (Kim and Lyon, 2011; Toffel and Short, 2011). Common explanations for such strategic behaviour include concealed benefits to firms that may (a) make overambitious claims about environmental performance (i.e. *greenwashing*) (Lyon and Maxwell, 2011; Millard-Ball, 2013; Wu, Zhang, and Xie, 2020; Cui *et al.*, 2022), (b) desire a softening of regulatory stringency (Innes and Sam, 2008; Li and Khanna, 2018), (c) avoid environmental controversies and the resulting reputational damage or social sanctions.[4]

Another strand of related literature has increasingly explored the value effect of firms' CSR disclosure practices. CSR disclosures encompass a broader range of reporting covering firms' Environmental, Social and Governance activities. The effect of CSR disclosure practices on firm value depends on whether the disclosure is mandatory or voluntary. Firms often engage in voluntary carbon disclosure practices to signal their higher-performing carbon performance (Luo and Tang, 2014; Datt, Luo, and Tang, 2019). Besides, given the unprecedented global demand for greater transparency about corporate environmental impact and performance by stakeholders (i.e. investors, regulators and environmental activists) (Hahn, Reimsbach, and Schiemann, 2015; Kim and Lyon, 2015), we envisage that the extent to which high-performing firms voluntarily disclose their emissions is contingent on the influence of these key stakeholders. Thus, we identify how the efficiency-disclosure relationship is conditioned by the above key stakeholders. Consequently, some studies have generally observed a positive effect between voluntary CSR disclosure and firm value (Mallin, Farag, and Ow-Yong, 2014; Li, 2017). Comparatively, a negative effect has been observed between CSR disclosure and firm value in mandatory settings (Chen, Hung, and Wang, 2018). The negative effect suggests that the benefits of mandatory CSR disclosure may be more long term and generate positive social externalities at the expense of shareholders (Chen *et al.*, 2018). Taken together, these studies demonstrate that the relationship between CSR disclosure and firm value is complex and may be influenced by various factors. Thus, there is a need to move beyond the debate in the literature and study other factors that may help to consolidate our understanding of firms' carbon disclosure behaviours.

To further existing research, we investigate the influence of technology on firms' voluntary carbon disclosure behaviours to investigate the possibility of a unique technology-disclosure relationship. As research has shown, there are reasons to expect that firm technologies and their carbon disclosure behaviours might be connected. For instance, it is well-recognized that firms make capital investments to mitigate legitimacy threats

[4]There is a strand of the literature linking environmental violations to firm reputation damage (Daubanes and Rochet, 2019).

that arise in the political environment in which they operate (e.g. Brown, Martinsson, and Petersen, 2012; Calel and Dechezleprêtre, 2016). One of these legitimacy threats is adherence to pro-environmental disclosure regulations, which has been bolstered by the rise in the global climate change discourse. Firms with higher levels of carbon emissions relative to a predetermined regulatory threshold are seen as engaging in illegitimate behaviour that goes against the pro-environmental norm. As a result, a firm may opt to undertake strategic investments in low-carbon technologies to enable meeting the requirements of carbon disclosure regulations and thereby avoid legitimacy threats (Acemoglu *et al.*, 2012; Chen, Song, and Wu, 2021). However, there is little empirical evidence on the extent to which investments in low-carbon technologies ultimately shape firms' carbon disclosure behaviours.

In this study, we contribute to the academic literature by empirically evaluating whether and how the energy efficiency of firm production technologies shapes the voluntary carbon disclosure behaviour of a large sample of firms. Unlike mandatory carbon disclosures prescribed by regulation, our analysis ensures that the sampled firms' disclosure behaviours are voluntary. Exploring this voluntary behaviour is vitally important given the limited prevalence of mandatory disclosures across only a few advanced economies (OECD, 2015). Moreover, our analysis of voluntary carbon disclosure fits the reality that unprecedented concerns about dangerous climate change are driving social concerns about the extent to which firms harm the environment and social welfare. This may be causing many of them to anticipate judgement by voluntarily disclosing their carbon impact as part of their corporate environmental, social and governance (ESG) disclosure strategy and transparency (Gillan, Koch, and Starks, 2021; Huang *et al.*, 2022; The Economist, 2022b). Our empirical strategy employs a three-stage approach. First, we characterize heterogeneity in the firm-level emission-generating technology by estimating technical energy efficiency (TEF) using stochastic frontier analysis (SFA).[5] Second, we estimate the effect of TEF on the probability that a firm voluntarily discloses its carbon emissions. Third, we uncover the moderating effects of key stakeholders (i.e. shareholders, regulators, and environmental activists) on the technology-disclosure relationship.

Our econometric approach addresses potential endogeneity issues caused by (a) unobserved variables that concurrently drive firm performance and carbon disclosure behaviour, as well as (b) reverse causation, in which disclosing the carbon footprint of firms' production operations may attract attention and pressure from the stakeholders mentioned above. We address the endogeneity issue by carefully constructing instrumental variables (IVs) for the TEF and the three stakeholder parameters. Our IVs exploit exogenous variations in global energy price shocks (for TEF), colonists' environmental policy (for environmental policy), the severity of country-level natural disasters (for climate activism), and shareholder revolts among other firms in the same country (for shareholder campaigns). To incorporate cross-sectional variation into the above

[5] The production frontier technique is a well-established approach for estimating technical and environmental performance of firm-level production technologies as an objective quantitative measure that is well-grounded in production theory. The approach estimates environmental efficiency by treating energy/pollution as an undesirable input that needs to be contracted within the production technology. For previous empirical applications, see Hiebert (2002), Färe *et al.* (2005), Murty et al. (2012) and Adetutu and Stathopoulou (2021). Subsequently, we compare this with a conventional TFP approach to evaluate robustness.

instruments, we interact the global and country-level instruments with the cost of debt at the firm-level. Therefore, as we elaborate in a subsequent section, these IVs combine global and national temporal shocks with cross-firm variation in the presample interest rates that banks set on firm-level borrowing.

We report three key findings. First, firms with the most efficient technologies for reducing emissions tend to disclose their carbon emissions. Given that the efficiency variable is an estimated regressor, we test the robustness of this finding using alternative measures of firm performance: total factor productivity (TFP) and labour productivity (Y/L). Second, firms with superior technologies appear to have a greater propensity to disclose their carbon emissions when faced with stringent environmental regulations. These high-performing firms demonstrate a tendency for non-disclosure when faced with intense shareholder and environmental activist pushback against pollution. Third, our findings highlight the existence of a profitability penalty for transparent high-efficiency firms relative to comparable firms that adopt strategic silence.

This study contributes to several strands of the literature. First, our paper is related to the literature on energy-saving technology, which documents the linkages between such technologies and a broad range of determinants and outcomes. This literature has looked at the various drivers of technological innovation, such as energy prices and carbon taxes (e.g. Popp, 2002; Acemoglu *et al.*, 2012; Aghion *et al.*, 2016), environmental regulation (Hascic *et al.*, 2008; Johnstone, Haščič, and Popp, 2010; Hatfield and Kosec, 2019), as well as those modelling the firm-level determinants of induced technological change in energy and climate change contexts (Cohen and Klepper, 1992; Klette and Kortum, 2004; Noailly and Smeets, 2015). We contribute to this literature by exploring the effect of firm energy technology type on their voluntary carbon disclosure behaviours.

Second, we argue that non-disclosure may characterize the data sample without a well-designed incentive mechanism. Theoretically, the lack of an incentive-compatible regulatory arrangement to elicit truthful information will plausibly result in nondisclosure (Perman, 2003, p. 258). Such behaviour is fundamentally an asymmetric information problem. Firms know more about their emissions than regulators, and stakeholders cannot observe the costly effort firms put into emissions reduction (See Montero, 1999, 2000; Martin, De Preux, and Wagner, 2014). There is little empirical work investigating firm disclosure incentives within a voluntary carbon disclosure programme. On the one hand, firms with superior technologies may be motivated to disclose their environmental performances to increase their market share or boost profitability (Clarkson *et al.*, 2008; Servaes and Tamayo, 2013). Such firms may also aim to showcase their environmental performance, believing that poor-performing competitors cannot easily imitate them (Krüger, 2015). On the other hand, unobserved environmental performance conveys invaluable information about firms' abatement potential and control costs (Adetutu and Stathopoulou, 2021). Therefore, firms may be reluctant to disclose private information about their production technologies, concerned that such disclosures will lead to stringent policies and weaken their bargaining position policy negotiations (Martin *et al.*, 2014). Our analysis overcomes the foregoing ambiguity by explicitly relating the unobserved environmental performance of firm production technologies to carbon disclosure decisions, thereby revealing firm technology efficiency as a crucial reason to participate in voluntary carbon disclosures.

Third, in this paper, we draw on two distinct theoretical viewpoints that inform voluntary disclosure strategies to offer much-needed understanding of how stakeholders moderate the technology-disclosure relationship. On the one hand, we draw on agency theory, which posits that a firm's voluntary disclosure strategies are shaped by agent characteristics (Jensen and Meckling, 1976). Thus, we include firm-level factors such as board characteristics, ownership structures, and firm age (e.g. Duflo *et al.*, 2013; Kim *et al.*, 2020). On the other hand, we also draw on legitimacy theory, which suggests that a firm's values reflect the level of scrutiny posed by the society in which it is located (Dowling and Pfeffer, 1975). Meanwhile, Carney (2019) has argued that climate risk transcends the horizon of most economic agents and advocated for greater transparency via increased activist and regulatory pressure on corporations. Moreover, the role of three critical stakeholders (i.e. environmental activists, investors and regulators) in shaping corporate environmental decisions has garnered significant interest in the global media (Financial Times, 2021; The Economist, 2022a) and academic research (Marquis, Toffel, and Zhou, 2016; Flammer, Toffel, and Viswanathan, 2021; Adetutu *et al.*, 2023). Hence, our study offers a more robust synthesis of how these stakeholders shape the technology-disclosure relationship.

The remainder of the paper is organized as follows. Section 2 presents the research design and hypotheses development. In section 3, we set out the study hypotheses that guide our empirical analysis and econometric framework. Section 4 presents our dataset and descriptive statistics. Section 5 reports the empirical results and discusses their robustness and alternative explanations. Section 6 concludes.

II. Research design and hypotheses development

The key target of this study is to estimate the probability of a firm disclosing its environmental performance and hypothesize that this is likely to be conditioned by its success in keeping down its emissions. The success or otherwise of the firm's emission reduction is, we further assume, conditional on the technical efficiency of its production processes. Consequently, we relate the voluntary disclosure probability to the firm's technical efficiency. In order to provide testable hypotheses for the empirical analysis, we construct a simple setup where firms decide whether to disclose their environmental performance conditional on the technical efficiency of their energy-using production technology. We write e for energy efficiency and M for emissions so that positive emissions are a decreasing function of energy efficiency: $M(e) > 0$; $M'(e) < 0$.

Following Zhang and Khanna (2024), we can write the firm's objective as to minimize its emissions-related cost, that is, the sum of the emissions cost arising from regulatory pressures, R, and the emissions cost due to pressures from key stakeholders such as the public, activists and shareholders, D.

$$\min\ C = R(M(e), p, \theta) + D(M(e), p, \lambda). \tag{1}$$

Both $R(\cdot)$ and $D(\cdot)$ depend on the level of emissions, which in turn depends on the firm's energy efficiency level. The impact of these variables is determined by whether the firm decides to voluntarily disclose its environmental performance which is represented as the binary variable, p, where $p = 0$ denotes the firm remaining silent and $p = 1$ represents the firm participating in voluntary disclosure. Additional variables that impact emissions-related costs are the effectiveness of the regulation pressure θ and the effectiveness of stakeholders' pressure λ, respectively. Therefore, we write the regulatory and stakeholder costs when firms remain silent as $R(M(e), 0, \theta)$ and $D(M(e), 0, \lambda)$ and the regulatory and stakeholder costs when firms disclose their emissions as $R(M(e), 1, \theta)$ and $D(M(e), 1, \lambda)$, respectively.

We assume that $\partial R/\partial\theta \geq 0, \partial R/\partial M > 0$. Namely that the more effective is the regulatory pressure, the higher is the associated emissions cost; and that the lower is energy efficiency (and hence higher emissions) the higher is the associated emissions cost, $\partial R/\partial e = (\partial R/\partial M)(dM/de) < 0$. Finally, we assume that $R(M(e), 1, \theta) < R(M(e), 0, \theta)$. If the firm does participate in emissions disclosure, the costs arising from the effectiveness of regulatory pressure are lower than are the regulatory pressure costs associated with remaining silent. Our reasoning for this assumption is the following. In general, the regulatory costs associated with emissions, disclosed or not, arise from independent monitoring of firms and the imposition of emissions taxes and penalties. Monitoring is likely to be more cost and time consuming if firms are suspected of remaining silent in order to conceal emissions. Additionally, to allow for voluntary disclosure, the emissions tax may take the form of an option contract, since this was the optimal incentive mechanism suggested by Laffont and Tirole (1993) to incentivize information disclosure. The option contract mechanism offers the firm a choice of making a commitment to achieve an emissions reduction target in return for a low emissions tax rate per unit that escalates rapidly for failure to fulfil, or making no commitment to emissions reduction but payment of a high emissions tax rate per unit that does not vary strongly with the level of emissions.[6] Firms with high energy efficiency will choose the first option while firms with low energy efficiency will choose the second.

For $D(\cdot)$, we make the following assumptions: $\partial D/\partial\lambda \geq 0, \partial D/\partial e = (\partial D/\partial M)(dM/de) < 0$. Thus, there is a higher associated emissions cost for a more effective stakeholders' pressure, and also a higher associated emissions cost for lower energy efficiency (and higher emissions). Finally, we consider the relationship between $D(M(e), 1, \lambda)$and $D(M(e), 0, \lambda)$, that is, the effect on emissions-related costs from stakeholders' pressure when the firm participates in disclosure and when it remains silent. In principle, the outcome could be ambiguous, because of the differing objectives of stakeholders such as equity owners vs. activists. There are two types of activists that are significant in trying to nudge or drive the decisions of management: these are environmental activists, who mainly operate through public or political action, and equity activists. Adetutu *et al.* (2023) particularly examine the role of the environmental activists. However, there is increasing impact from equity activists, which are investment funds that take an equity stake in a firm, for example, an oil company, in order to change the direction of management decisions directly. Such equity activists are currently focused on imposing emissions reduction targets on large emitters, Carney (2019). Therefore, activism towards reducing emissions may come from both public groups and within the group of shareholders. For this reason, we argue that potentially

[6] We present in the Data S1 a model of such an incentive mechanism.

$D(M(e), 1, \lambda) < D(M(e), 0, \lambda)$. However, the effect may be ambiguous if the relative strengths of the activists, both public and activist shareholders, and the established shareholders are finely balanced.

In summary, for a firm to disclose, emissions costs need to be lower from participating in the voluntary disclosure programme than not. Based on the *a priori* arguments above, this would require

$$R(M(e), 1, \theta) + D(M(e), 1, \lambda) < R(M(e), 0, \theta) + D(M(e), 0, \lambda) \tag{2}$$

From (2), focusing on the effect of regulatory pressure, we can see that a more stringent regulation would increase the associated cost, $R(\cdot)$. Given that $R(M(e), 1, \theta) < R(M(e), 0, \theta)$, the inequality would be satisfied and hence we can hypothesize that.

H1. A higher-efficiency firm is more likely to disclose its carbon performance when faced with more stringent environmental regulations.

In the case of increased pressure from key stakeholders, from (2), we can postulate that a higher-efficiency firm disclosing its environmental performance may give rise to costs due to scrutiny of participants by the public or activists, or increased pressures from established shareholders to do more, so that the public image of the firm is further improved. In such a case, a firm could choose strategic silence to reduce these costs from participating in a voluntary disclosure scheme. This leads us to.

H2. For a higher-efficiency firm, intense pressures from key stakeholders to perform better in terms of environmental performance make it more likely that it chooses strategic silence.

Combining the two hypotheses, we can see that generally a higher-efficiency firm would more likely choose disclosure as long as the reduction in the regulatory pressures emissions cost from being a higher efficiency firm outweighs the reduction in the stakeholders' pressures. In such a case, we can hypothesize the following.

H3. A higher-efficiency firm would more likely choose to disclose its carbon performance.

Consequently, we can empirically test the critical relationship between energy efficiency and firm disclosure probability with our three hypotheses informing our empirical investigation.

III. Empirical framework

Characterizing the performance of firm energy technology

We characterize firm technology by the energy efficiency of its production technology. The use of TEF as a proxy for firm-level energy technology is timely and justified, given that many corporations now make improvements in the energy efficiency of their production technology the centrepiece of their CSR credentials. Hence, in our first empirical work, we estimate the energy efficiency of the firm-level emission-generating production technology using parametric SFA, a common approach for estimating the technical efficiency of productive units (see Knittel, 2002; Asche, Roll, and Tveteras, 2009; Kumbhakar and Tsionas, 2011, 2016). The basic assumption behind the SFA model is that firms can potentially attain production optimization. Under this approach, the core idea of efficiency measurement is that while statistically there is no such thing as 'inefficiency' it is possible to rationalize the decomposition of the regression random errors to identify an element that can be defined as inefficiency. We do this by making use of the properties of random variables with known probability distributions. The residual can be decomposed into two random variables: (i) a symmetrically distributed term, treated as the traditional idiosyncratic error term and (ii) an asymmetrically distributed error term. Using economic reasoning, we can interpret the asymmetrically distributed random variable as 'inefficiency' – provided the asymmetry is in the right direction, that is, negatively skewed for production or input distance function data. The reasoning is as follows.

It begins with the expected relationship between outputs and inputs for the *frontier* firms. Observations of input usage below the input distance frontier correspond to inefficient organisations. The assumed shape of the distribution suggests that larger degrees of inefficiency are less probable than smaller degrees of inefficiency, that is, that a part of the error term has a low probability of a highly negative value and a high probability of a low negative value. Most firms can be expected to be close to the efficient frontier and therefore display low values of inefficiency. A minority of very poorly performing firms can be expected to be far below the efficient input distance frontier, displaying high values of inefficiency. The overall error distribution represents the summation of these preceding effects: the two-sided random error of the standard regression model and the one-sided error term capturing inefficiency. The combination of the two error terms (sometimes called the composed error model) is labelled SFA. This suggests that deviations from the frontier regression are due to both inefficiency and random error (measurement error, omitted variables and specification error). The resulting distribution is skewed below the frontier input distance function.

With the SFA model, two advantages arise. We can estimate a frontier that itself includes the usual regression random error term, and we can explicitly test for the presence of inefficiency and measure its contribution to the residuals. These tests and measures are related to how skewed SFA compares to OLS. The price of being able to do this is that we must make an explicit assumption about the shape of the inefficiency distribution. We can note two helpful factors, however. The form of the relationship between the dependent variable and the explanatory variables is entirely unaffected by the application of this model – it is identical to the standard regression model, nor does it not require any additional data collection or assumptions about the nature of the data beyond those required for the standard regression model.

However, endogeneity is also a critical issue in measuring efficiency and productivity in the production technology and a variety of approaches exist to address this. Initially, researchers ignored the distinction between the components of the composed error that is the key aspect of SFA. Olley and Pakes (1996) assumed that firms' choices of input quantities depend on output per unit of inputs consumed, that is, their productivity, and they developed an algorithmic approach to address this. Levinsohn and Petrin (2003) extended the procedure in Olley and Pakes who had used investment to control for correlation between input levels and the unobserved firm-specific productivity process. Levinsohn and Petrin argued that intermediate inputs can also solve this simultaneity problem. These authors, however, addressed endogeneity in a non-frontier context. In other words, they assumed that firms efficiently operated on the production frontier. This is not sufficient to achieve our objectives in this paper. Consequently, these earlier approaches treat the error term in the production function (or its equivalent) as a single rather than a composite error, as shown in the surveys by Kutlu and Tran (2019) and Orea and Zofío (2017), who also point out that models that do not explicitly separate the idiosyncratic and inefficiency components of the error term can generate bias and inefficiency in the resulting estimators. A number of approaches have been developed to address the endogeneity issue in the context of the stochastic frontier model.

Karakaplan and Kutlu (2017a, 2017b), Kutlu and Tran (2019) and Orea and Zofío (2017) all use a general framework in which the production technology is modelled as a stochastic frontier with a composed error term and the endogenous variables in the frontier are then written as reduced form functions of IVs and additional idiosyncratic errors. Endogeneity arises if the error terms in the reduced form equations for the endogenous variables are correlated with the composed error terms in the frontier model. In this paper, we have used the Maximum likelihood (ML) with IVs approach of Karakaplan and Kutlu (2017b) who explicitly address the correlation of both of the error components measuring inefficiency and random error in the production technology with the error terms in the reduced form equations for the endogenous variables. Endogenous variables are defined in two categories: endogenous variables in the production technology (represented in our case by the input distance function conditional on outputs) and endogenous variables that determine the expected value of the inefficiency error component. The Karaplan and Kutlu approach derives a composite log likelihood function incorporating the IVs into the frontier specification and shows how they can comprise an endogeneity-bias correction factor for the input distance function. We explain in detail in Appendix B exactly how we made our choice of the IVs to address the endogeneity issue in the SFA. Appendix B also provides a detailed theoretical background on our SFA approach to computing firm-level TEF. Given that the efficiency variable is a constructed regressor, we check the robustness of our results to alternative measures of firm performance such as TFP and labour productivity (Y/L).

Measuring the effect of energy technology on disclosure behaviour

In our baseline empirical analysis, we start by assuming that a firm's carbon disclosure decision is a function of the energy efficiency of its production technology, a set of firm-specific characteristics, and country-level variables, such that:

$$\text{Prob}\,(\text{Disclosure}_{it} = 1) = \text{f}\,(\text{TEF}_{it}, \boldsymbol{X}_{it}, \boldsymbol{X}_{ct}), \tag{3}$$

where the subscript i denotes the firm, c denotes country, and t represents year, Disclosure_{it} is a dummy variable coded as 1 if the ith firm has voluntarily publicly disclosed its carbon emissions and coded as 0 otherwise. TEF_{it} is our key independent variable characterising the firm's production technology. $\mathbf{X}_{it}$ is a vector of firm-level characteristics obtained from the Refinitiv database. Within the firm-level controls, we draw on the theoretical idea that a firm's voluntary disclosure behaviour is determined by agent characteristics (Jensen and Meckling, 1976; Duflo *et al.*, 2013). Additionally, we take cognizance of the fact a firm's corporate governance often shapes management practices, especially those relating to public disclosure decisions (Johnson, Ryan, and Tian, 2009; Kim *et al.*, 2020). Thus, we include firm-level factors such as firm age and size, as well as relevant corporate governance variables such as CEO duality and board diversity. $\mathbf{X}_{ct}$ is a vector of country-level controls such as GDP growth and institutional quality. See Table C1, which provides more information on our data including the variables, their definitions and sources.

Given that our objectives go beyond establishing a technology-disclosure relationship, we are also interested in examining the moderating effects of stakeholders on the technology-disclosure nexus. Such additional analysis is vital to understanding if and how stakeholders shape the disclosure incentives of firms with different emissions-producing technologies (i.e. to capture the disclosure incentives of high-efficiency firms relative to their low-efficiency counterparts). We, therefore, add to our baseline model the three previously discussed stakeholders relating to environmental regulation, environmental activism, and shareholders, along with their interaction terms with TEF_{it}:

$$\text{TEF}_{it} \times \text{Regulation}_{ist}$$

$$\text{TEF}_{it} \times \text{Activism}_{it}$$

$$\text{TEF}_{it} \times \text{Shareholder}_{it}$$

where Regulation_{ist} is a sector-country level measure of the stringency of environmental regulation and Activism_{it} captures the intensity of environmental activism facing each firm in our sample. Finally, Shareholder_{it} is the total number of firm-level environmentally related controversies/negative media coverage arising from shareholder campaigns and agitations. The above interaction terms constitute key coefficients of interest that allow us to identify the role of production technology heterogeneity as a determinant of firm carbon disclosure decisions in the presence of stakeholder interventions.

IVs analysis

The main empirical challenge in estimating the above technology-disclosure relationship is the potential endogeneity of the technical efficiency variable. Though we include a range of control variables in our model, unobserved heterogeneity could still cause the omitted variable bias. Moreover, we cannot rule out reverse causality running from carbon disclosure decisions to the efficiency variable. Therefore, we use an IV-probit estimator to alleviate the endogeneity concerns.

Following the well-established theoretical and empirical literature (e.g. Popp, 2002; Acemoglu *et al.*, 2012; Aghion *et al.*, 2016; Gillingham and Tsvetanov, 2019), we use the out-of-sample variations in energy prices as instruments for energy efficiency. Our *a* *priori* theoretical reasoning is as follows. First, an attractive feature of energy prices is that they are often driven by exogenous shocks (e.g. natural disasters and geopolitical events[7]) outside the control of the firms in our data sample.[8] Second, firms tend to innovate in energy-saving production techniques and processes when faced with higher fuel prices (Newell, Jaffe, and Stavins, 1999; Acemoglu *et al.*, 2012; Arvanitis and Ley, 2013; Aghion *et al.*, 2016). Conversely, higher renewable prices can slow the energy transition process by increasing production costs, driving uncertainty and creating technological risks (Reguant, 2014; Ye, Paulson, and Khanna, 2022). Thus, fossil fuel and renewable energy prices are relevant predictors of energy efficiency. We use oil prices as a proxy for fuel prices and the levelized cost[9] of renewable energy technology as a proxy for renewable energy prices, obtained from the EIA and IRENA databases, respectively. Apart from being exogenous, we expect the energy price variables to satisfy the exclusion restriction, to be orthogonal to the error term in a second-stage regression. The reason is twofold.

First, there is a very large body of work documenting that energy price shocks are transmitted into firm productive performance through cutbacks in investment expenditures and rising marginal cost of production that cause firms to adjust down their capacity utilisation and reduce production (Hamilton, 2008; Sadath and Acharya, 2015; André *et al.*, 2023). Research has shown that these cost effects shape firm competitiveness, incentivizing capable firms to innovate and boost energy efficiency and productivity (Fontagné, Martin, and Orefice, 2023; Zhou *et al.*, 2023).

Second, even if it may be possible that the energy price IVs are related to some other confounding variables such as public environmental concerns and stakeholders' strategies, a benefit of our empirical strategy is that these variables are measured as covariates on the right-hand side of our model, yielding projected values from which the causal effect of energy efficiency on firm disclosure can be determined. Hence, the energy price variables serve as exogenous shocks that should not directly affect carbon disclosure except through its effect on production and the underpinning energy efficiency of its technology. We provide some empirical evidence to support this assumption by conducting a placebo analysis where we estimate the effect of non-energy prices (i.e., core inflation) on carbon disclosure behaviour using our full data sample and a restricted data sample of highly indebted firms. The results provided in the Table E1 suggest that non-energy prices have no statistically significant effect on carbon disclosure decisions. The causal channel between energy prices and firm decisions is well established in the production function literature (Berndt and Wood, 1975; Fuss, 1977; Ganapati, Shapiro, and Walker, 2016; Kim, 2017). More specifically, this literature shows that energy directly enters into the production function through the firm utilization of its capital stock (Finn, 2000). Thus, the efficiency of this capital stock is the relevant entry-point in the energy-output relationship.

[7] The ongoing Russia-Ukraine conflict is a timely example of such geopolitical events. The idea of energy price shocks arising from exogenous events is also well documented in the literature (Cunado *et al.*, 2020; Wen, Zhao, and Chang, 2021).

[8] The idea that energy prices are exogenous to firm-level production, technology and energy intensity/consumption is tested and well established in the literature (see Linn, 2008; Martin *et al.*, 2014).

[9] The levelized cost of energy (LCOE captures the average cost per unit of energy generated across the lifetime of a new power plant. It is measured in US$ per kilowatt-hour. It is the lifetime cost of the plant divided by its energy production (US$ per kilowatt-hour).

TABLE 1
Summary statistics

	Mean	*SD*	*Min*	*Max*
Disclosure (dummy)	0.172	0.378	0	1
Output (real USD)	5.097e+09	2.389e+10	0	5.150e+11
Net capital stock (real USD)	4.524e+09	2.004e+10	−94,106,152	5.106e+11
Labour (number of employees)	10,883.234	31,527.51	2	552,755
Energy use (GWh)	1,192,037.1	6,840,374.89	0.85	1.967e+08
Total asset (real USD)	7.356e+09	2.787e+10	3,356,601.5	6.637e+11
Firm age (years)	44.151	34.454	2	204
Return on asset (ROA) ratio	0.048	0.246	−30.959	8.449
CEO age (years)	51.907	8.780	25	91
CEO duality (dummy)	0.147	0.354	0	1
Average board tenure (years)	6.080	3.954	0.8	37.9
Board diversity (%)	5.465	9.226	0	62.5
Number of shareholder controversies	0.011	0.179	0	8
Number of activist clashes	1.578	2.392	0	18
Environmental stringency index	1.902	0.913	0.375	4.133
Real economic growth (%)	3.808	4.129	−8.07	25.16
Control of corruption index	0.874	0.952	−1.13	2.47
Fuel price (real USD)	73.71	23.21	35.86	109.72
Renewable energy price (real USD/kWh)	0.258	0.106	0.092	0.407
Interest (%)	2.090	2.48	0.410	11.58
Colonial environmental tax (%)	2.291	0.625	1.240	4.85
Natural disaster deaths (persons)	2,732.25	12,548.16	0	88,450
Other firms' shareholder revolts (no.)	1.804	3.809	0	23

This energy efficiency is what we have in mind, and that we measured using the SFA model. If energy prices are high, the firm faces higher relative energy prices, necessitating a production decision on whether to use a more energy-efficient production process or vice versa. Hence, the first effect of energy price variation on firm output is that it triggers a production decision. Even if a firm would disclose its emissions due to changing energy prices, it is plausibly because such price changes have triggered technical improvements that are worth showcasing to stakeholders. In essence, firms are very unlikely to simply disclose their carbon effect on account of changing energy prices.

However, while the energy price variables have the desirable property of exogeneity, they lack cross-sectional variation across sampled firms who all face the same prices. Thus, we need a firm-level variable that predicts energy efficiency but is not directly related to carbon disclosure decision or other unmeasured confounding factors. To this end, we use firm-level interest rates to adjust the energy price variables. We compute this measure as the ratio of firm-level interest expense to total debt (multiplied by 100%). As shown by the descriptive statistics (Table 1), the standard deviation of firm-level cost of debt is 2.48%, which, when compared to the mean value (2.09%), indicates a high degree of variability in the data across the sampled firms. This substantial variation is consistent with the fact that the sort of firms in our data sample frequently have several firm-bank relationships (Farinha and Santos, 2002; Ioannidou and Ongena, 2010), allowing them to change their debt costs (Schwert, 2020).

Our identifying assumption is that technological innovation is often needed to improve the energy efficiency of firm production methods[10] (Noailly and Smeets, 2015; Aghion *et al.*, 2016; Lazkano, Nøstbakken, and Pelli, 2017). Yet, innovation is an expensive process requiring significant financial resources (see Kamien and Schwartz, 1972; Van Elkan, 1996; Kerr and Nanda, 2015; Giebel and Kraft, 2020). Moreover, such technological advances can face significant challenges stemming from uncertainty about innovation success and the time lags between innovation expenditure and their outcome (Bergemann and Hege, 2005; Manso, 2011).

On account of the aforementioned difficulty, the finance literature documents that innovation is sensitive to credit supply, reflecting the difficulty to secure external financing to support innovation activities (Brown, Fazzari, and Petersen, 2009; Brown *et al.*, 2012; Giebel and Kraft, 2020). A strand of this literature shows that external financing constraints mean that innovation investments are inversely related to the cost of debt (Chava, 2014; Zheng, Wang, and Xu, 2018; Giebel and Kraft, 2020; Saidi and Žaldokas, 2021). Therefore, studies have shown that the high cost of capital is associated with the 'energy efficiency gap' (Gerarden, Newell, and Stavins, 2017). For instance, research provides micro-econometric evidence that loan interest rates shape firm access to finance and thus energy efficiency improvements (Fan *et al.*, 2021; Lee, Wang, and Chang, 2023; Wang and Lee, 2023). Hence, we expect firm-level interest rates to be correlated with energy efficiency. These interest rates are determined exogenously by financial markets or banks aiming to maximize their profits by setting interest rates over the benchmark policy rates prescribed by central banks. In setting their lending rates, banks are also known to apply their own (i.e. managers') firm-specific assessments of the riskiness of innovation projects (Allen and Gale, 1999; Allen, Gu, and Kowalewski, 2018; Fan *et al.*, 2021).

Intuitively, there is no direct causal basis for a firm to disclose its carbon impact on account of the interest rate on its debt. Thus, a reasonable indirect mechanism is that the cost of debt will have implications for efficiency innovation and advances in production techniques that may then encourage carbon disclosure. Thus, our approach using the interest rate variable preserves the exogeneity of the energy price IVs, which are formally defined as:

$$\text{Fuel price}_{i,t} = \text{Fuel price}_{w,t} \times IR_i,$$

$$\text{REN price}_{i,t} = \text{REN price}_{w,t} \times IR_i,$$

where $\text{Fuel price}_{w,t}$ and $\text{REN price}_{w,t}$ are, respectively, global oil and renewable prices (real US$) in year t. IR_{it} is the average interest rate of firm i.

IV. Additional instruments

We cannot assume that there is exogenous variation in the stakeholder measures. For instance, activist pushback may be conditioned on the disclosure behaviour of sampled

[10] This may involve the upgrade or replacement of the energy-using capital stock.

firms. Moreover, the stakeholder variables might be correlated with omitted variables. Hence, we estimate a model specification in which we instrument for each of the three stakeholder variables in addition to instrumenting for the efficiency variable. As instruments, we use colonizer's environmental regulation (for regulation), natural disasters (for activism) and the total number of shareholder activist campaigns relating to firms in other industries located in the same country in year t. The construction and identifying assumptions supporting the instruments are discussed in the following sub-sections.

Colonist's environmental policy

To instrument for environmental regulation, we use the environmental tax variable (as % of GDP) of the colonial master of each country in which a firm is located. For countries that were never colonized, we use the environmental tax variable of any foreign country that had previously successfully invaded such country. For example, although the Netherlands was never colonized, it succumbed to French conquest or annexation from 1795 to 1814.[11] Hence, we use the French tax variable for the Netherlands. The identifying assumptions underpinning the suitability of the colonist tax rate instrument is twofold.

First, countries' policies are often correlated or influenced by their colonial history, even long after they have attained political independence (Glaeser and Shleifer, 2002; Anderson, 2018). This path dependence is present in environmental regulation (see Fredriksson and Wollscheid, 2015; Ang and Fredriksson, 2017). Second, besides the correlation argument, path dependence offers an exogenous shock to country-level policies considering that colonization is usually a forceful venture in which political control is imposed via military conquest (see McNeill, 2015). Moreover, the involuntary submission to external control implies that the colonized country hardly has any choice of self-selection into colonization, thereby ensuring that the instrument is uncorrelated with the error term. Ultimately, the exogeneity argument is made even more likely due to the reality that, for all the countries in which sampled firms are located, the reference colonial period and the political independence dates predate the study period. Hence, the colonisation horizon is predetermined and should be orthogonal to the error term in a second-stage regression.

Natural disasters

To address the potential endogeneity of the activist variable, we use natural disasters as shocks to the incidence and intensity of activist campaigns. We argue that the last few decades have witnessed heightened concerns about climate change risk, as exemplified in the rising severity and frequency natural disasters (Intergovernmental Panel on Climate Change (IPCC), 2012; Coronese *et al.*, 2019).

Research indicates that the significant media coverage of natural disasters can trigger emotional responses such as protests and activist campaigns (Uzzell, 2000; Bonaiuto *et al.*, 2016; Checker, 2017). For example, victims of natural disasters can be enraged by the damage from disaster events, causing them to coalesce into collective action and

[11] See Callister (2017).

protests, especially when they believe the damage could have been mitigated or prevented (see Rochford Jr and Blocker, 1991; Whitmarsh, 2008). Hence, research shows that a key determinant of environmental activism is the perception that governments are not acting with adequate determination to address climate change (Adetutu *et al.*, 2023; Besley and Persson, 2023).

Furthermore, a notable feature of natural disasters is their suddenness, ensuring that their timing or probability is exogenously determined by the forces of nature such as geography and meteorology. Moreover, even if sampled firms were broadly concerned about the rising incidence of natural disasters, we do not expect such concerns to directly affect carbon disclosure, except through how such disaster events cause activists to apply pressure on firms. This assumption is due to how we construct the disaster IV, which we discuss as follows.

First, we exploit the geo-location information on the activist campaigns and natural disasters, available from the EJAtlas and the international disaster database EM-DAT,[12] respectively. Second, our data matching scheme links natural disasters and activism by matching disasters occurring in the same province to activist campaigns relating to firms other than the disclosing firm. This ensures that disasters affect the broad sector-location level (i.e. firm-excluded) activist sentiments with no direct relation to the firm's production activities. The indirect channel of impact is that increased activist campaigns will plausibly cause firms to become concerned that they could also be targeted by activists in a way that influences carbon disclosure. Finally, the disaster data from EM-DAT is the total number of deaths arising from natural disasters occurring in the province/district where activist campaigns were held.

Other firms' shareholder campaigns

We propose a further instrument to deal with potential endogeneity of the shareholder campaign variable: the total number of climate shareholder revolts across all firms in the country of operation other than the firm in question. This instrument is an exogenous shock caused by the conditions of other enterprises, which reduces the possibility that it is correlated with unobservable factors in each of the reference firms. Turning to the instrument's relevance, research has shown that group backlash can be an emotional activity in which people obtain psychological fulfilment from joining other groups to express their grievances (Passarelli and Tabellini, 2017).

Hence, shareholders of a specific firm may be motivated to join other firms' shareholders in pushing back against the ecological impact of firm production activities (see Reuters, 2021; Washington Post, 2022). To this end, studies have employed, as instruments, geographical- and industry-based variables covering firms other than the firm in question (Xiong *et al.*, 2021; Cao, Wang, and Zhou, 2022). Finally, as with the energy price instruments, the above-three instruments have no cross-sectional variation because they are location-based measures, which means that various enterprises in a country will have the same location-based instruments due to their shared exposure. To this end, we impose cross-sectional variation on the instruments by using each firm's presample age

[12] https://www.emdat.be/.

in 2000. Using the predetermined age permits us to maintain the IV's exogeneity. At the same time, firm age is a good predictor of firm-stakeholder relationships, because older enterprises are likely to have larger carbon footprints, making them more vulnerable to stakeholder pressures (Wagner, 2011) and more capable of dealing with such pressures (Jo and Harjoto, 2012).

V. Data

Main dataset

To construct our core data, we extract all information relating to firm-level carbon disclosures and their production and financial variables from the CDP[13] and the Thomson Reuters Refinitiv (Eikon API) database. We note that our analysis is focused on firm voluntary carbon disclosure rather than mandatory disclosures prescribed by regulation. Hence, the CDP is a voluntary disclosure scheme. To obtain unobserved firm energy efficiency performance, we estimate an SFA model using the information on firm-level output (i.e. operating turnover), capital (i.e. net fixed assets), labour (i.e. number of employees) and energy use (i.e. electricity and fuel).

Other data

We control for several firm-level and country-level factors. At the firm-level, we include firm age and size (i.e. total assets) collected from the Eikon database. To analyse the determinants of reporting behaviour, we introduce measures of stakeholder pressure relating to regulators and social actors (i.e. environmental activists and shareholders). More specifically, we proxy environmental regulation by the annual environmental policy stringency (EPS) that each firm faces in its operating sector-country, taken from the OECD environmental statistics database. The EPS is an internationally comparable measure of the degree to which environmental policies penalize pollution. Environmental activism is observed at the firm-level and computed as the total number of clashes between corporations and environmental activists in a given year, obtained from the Environmental Justice Atlas (EJAtlas[14]) (Temper, Del Bene, and Martinez-Alier, 2015). Finally, $Shareholder_{it}$ is the total number of environmentally related controversies arising from shareholder campaigns and agitations. This variable is obtained from the Eikon Refinitiv dataset. Finally, we include country-level controls such as real GDP growth and institutional quality.

Descriptive statistics

Our final data sample includes 21,912 firm-year observations based on 1,547 energy-intensive corporations (193 petroleum, 1,174 industrial and 180 utilities) across 24

[13] See https://www.cdp.net/en.
[14] https://ejatlas.org/.

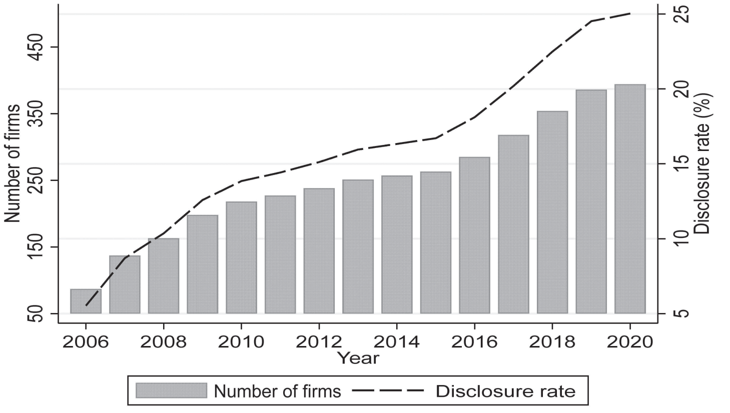

Figure 1. Evolution of carbon disclosure
Notes: pooled data covering number of sampled firms disclosing their carbon emissions during each year of our sampling period, along with the ratio of disclosing firms to total number of sampled firms (*Source*: Eikon Refinitiv Database)

countries[15] from 2006 to 2020. This final data sample is due to data availability within the Eikon database. Our data construction begins with the entire universe of firms within the database, from where we dropped firms with missing data observations on our key variables (e.g. production function and emission variables) across all sample periods. We then retain only firms observed during at least three sampling periods to allow us to conduct our efficiency and productivity change analysis that characterizes firm production technologies. Figure 1 shows the overall voluntary carbon disclosure incidence and trend across our data sample. In 2006, 87 of the 1,547 firms in our data sample made carbon disclosures, representing a disclosure rate of 5.5%. The incidence of carbon disclosure rose steadily over the study period, reaching 394 firms in 2020, equating to a 25% disclosure rate. The disclosure rate began rising sharply around 2016, after the Paris climate change agreement was signed in 2015, coinciding with the intense global pushback against environmental externalities.[16] Table 1 contains the descriptive statistics for the entire dataset. The disclosure incidence is a dummy variable, with a mean of 0.172 and a SD of 0.378, implying good variability in the disclosure behaviour across sampled firms.

VI. Results

Production frontier results

The SFA estimation results from the production frontier are presented in Table 2. Given that we adopt an input-oriented distance function, and to ensure the reliability of estimates, we address the possible endogeneity arising from specifying firm output as a right-hand

[15] Belgium, Brazil, Canada, China, Czech Republic, Denmark, Finland, France, Germany, Hong Kong, India, Republic of Ireland, Italy, Japan, South Korea, Netherlands, Norway, Portugal, Russia, Spain, Sweden, Switzerland, United Kingdom, United States. These countries jointly account for over 70% of global GHG emissions. See UNEP (2020).

[16] The last decade has witnessed an upsurge in the global environmental justice movement, as evidenced by increasing intensity and frequency of clashes between environmental activists and firms. See https://ejatlas.org/.

TABLE 2

Estimated production frontier parameters

Dependent variable: −ln (Energy)	*Model EX*	*Model EN*
Constant	−0.620***	0.116***
	[0.015]	[0.015]
ln Y	−0.795***	−0.435***
	[0.003]	[0.028]
ln K	0.396***	0.299***
	[0.004]	[0.009]
ln L	0.534***	0.647***
	[0.004]	[0.010]
Time	−0.021***	−0.033***
	[0.001]	[0.002]
Dependent variable: ln ($\sigma^2{}_u$)		
Constant	0.350***	0.037
	[0.073]	[0.087]
Energy price	−2.704***	−3.494***
	[0.138]	[0.247]
Dependent variable: ln ($\sigma^2{}_V$)		
Constant	−0.407***	
	[0.011]	
Dependent variable: ln ($\sigma^2{}_W$)		
Constant		−0.399***
		[0.010]
η		−0.366***
		[0.028]
η endogeneity test ($\chi^2 = 174.14$)		$P > \chi^2 = 0.000$
First stage regression		
Output price		0.012***
		[0.001]
Kleibergen Paap F-test		201.73
		[0.000]
Observations	21,912	21,912
Log-likelihood	−27,193.33	−70,001
Mean technical efficiency (TEF)	0.842	0.902

Note: SEs are in parentheses.
***, **, and ** denote statistical significance at 0.1%, 1%, and 5% levels, with heteroskedasticity-robust standard errors in parenthesis.

side (RHS) variable within the production frontier (Griffiths and Hajargasht, 2016) (see Data S1 for details and discussions). In column 1, we present the exogenous model that ignores the endogeneity of the RHS output variable, while column 2 contains the model that corrects for endogeneity bias arising from specifying the energy input, using sector-country level producer price index as exogenous shocks to firm-level production decisions. The exogenous 'Model EX' embodies a downward bias in the output elasticity, supported by the η endogeneity test statistic, which rejects the null hypothesis that firm output is exogenous at 0.1%. Thus, the endogeneity correction helps us to address attenuation bias. In this light, our first-stage results strongly support the hypothesis that higher output prices stimulate firm-level output. The F-stat of 201.73 on the instrument far exceeds the critical value of 10.

Focusing now on the preferred endogenous model, we note that the point estimates for the output and input elasticities are statistically significant at the 1% level. They are consistent with *a priori* expectations, given that the positive input (negative output) elasticities reflect that the input distance function essentially seeks to contract the input vector proportionally, holding the output vector fixed. The efficiency scores also reflect the attenuation bias arising from the endogeneity problem, considering that the mean energy efficiency index from the endogenous model is 0.902, compared to 0.842 in the exogenous model. Hence, sampled firms are more efficient than the standard exogenous model would suggest. See the graphical comparison of the distribution of the two efficiency scores in Figure B1, which bears out this observation. The average energy efficiency estimate from the endogeneity-adjusted model suggests that the typical firm in our sample demonstrated a 10% inefficiency in energy use, suggesting that such firms could potentially reduce their energy use by 10% relative to the best practice production technology.

Baseline results: technology, stakeholder pressure and carbon disclosure

Table 3 presents the baseline marginal effects of firm-level energy efficiency on carbon disclosure decisions. We report bootstrapped SEs, which are preferred, given that they account for the fact that the energy efficiency measure (TEF) is an estimated or constructed regressor. We start in column 1 with a basic specification that includes TEF (i.e. energy efficiency) but not yet the control variables and the fixed effects. The efficiency coefficient is positive and statistically significant at the 1% level, suggesting that firms with superior production technologies have a higher probability of publicly disclosing their carbon emissions. This finding is consistent with the notion that firms possessing more energy-efficient production technologies will likely showcase their environmental performances to gain a range of benefits relating to higher profitability and increased market share. In column 2, we build on our basic model specification by introducing control variables and sector-specific and country-specific time trends. The marginal effect of energy efficiency decreases in magnitude but remains statistically significant at the 1% level.

Our objectives go beyond establishing the technology-disclosure relationship. We are also interested in investigating stakeholders' roles and understanding how they shape firm disclosure decisions for a given level of technology. Therefore, in columns (3)–(5), we estimate a similar specification as in column (2) but add interaction terms between energy efficiency and the three stakeholder variables (i.e. environmental regulation, shareholder environmental events, and environmental activism) sequentially (one by one). Rather than interpreting the marginal effects directly, it is more instructive to consider the overall effects implied by the stakeholder coefficients assessed at the mean of our data sample. We thus report the overall effects of TEF and the stakeholder variables in the bottom (Panel B) of Table 3. In the results in columns (3)–(5), we note that the efficiency effect remains qualitatively stable. The overall effects indicate a tendency for highly efficient firms to report their carbon emissions in stringent regulatory regimes. By contrast, high-performing firms are less likely to disclose their carbon when operating in hostile conditions arising from intense environmental activism and shareholder campaigns.

TABLE 3

Baseline results

Dep. var. Firm disclosed carbon	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Panel A: Marginal effects						
TEF	0.380***	0.215***	−0.136***	0.218***	0.172***	−0.113***
	(0.034)	(0.024)	(0.034)	(0.020)	(0.027)	(0.0371)
Regulation			−0.200***			−0.165***
			(0.018)			(0.018)
Shareholder				0.222**		0.287***
				(0.113)		(0.106)
Activist					−0.050**	−0.039***
					(0.020)	(0.015)
TEF × Regulation			0.235***			0.197***
			(0.020)			(0.020)
TEF × Shareholder				−0.259**		−0.333***
				(0.119)		(0.109)
TEF × Activist					0.046**	0.038**
					(0.022)	(0.017)
Firm age		0.000***	0.001	0.000***	0.001**	0.000
		(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Firm size		0.070***	0.069***	0.070***	0.070***	0.070***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Board tenure		−0.001	−0.000	−0.001	−0.001	−0.000
		(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
CEO duality		0.018***	0.028***	0.018***	0.020***	0.028***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Board diversity		0.005***	0.005***	0.005***	0.005***	0.005***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Institutional quality		0.045***	0.040***	0.048***	0.043***	0.040***
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
GDP growth		−0.006***	−0.005***	−0.006***	−0.006***	−0.005***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Panel B: Overall effects						
TEF			0.393***	0.216***	0.223***	0.368***
			(0.003)	(0.021)	(0.021)	(0.029)
Regulation			0.014***			0.014***
			(0.003)			(0.002)
Shareholder				−0.015		−0.016**
				(0.011)		(0.007)
Activist					−0.007***	−0.004***
					(0.001)	(0.0010)
Firm effect	—	Yes	Yes	Yes	Yes	Yes
Year effect	—	Yes	Yes	Yes	Yes	Yes
Sector-specific time effect	—	Yes	Yes	Yes	Yes	Yes
Country-specific time effect	—	Yes	Yes	Yes	Yes	Yes
Log-likelihood	−9,996.40	−4,149.81	−4,057.73	−4,147.58	−4,098.17	−4,030.50
Pseudo R-squared	0.007	0.588	0.597	0.588	0.593	0.600
Observations	21,912	21,912	21,912	21,912	21,912	21,912

Notes: This table contains marginal effects and overall effects from probit regressions. The dependent variable in each regression is a dummy variable that takes the value of 1 when a firm discloses its carbon emissions in each period. Bootstrapped SEs in parentheses (100 replications).

* $P < 0.1$, **$P < 0.05$, *** $P < 0.01$.

In column (6), we present the full model specification by simultaneously including the three interaction terms. Our results hold when exploring this alternative model specification as the sign patterns and statistical significance are consistent with the previous results in columns (3)–(5). Specifically, the effect of efficiency indicates that a 1% increase in energy efficiency leads to a rise in the probability of carbon disclosure by 36.8% ($p < 1\%$). For firms operating in stringent regulatory regimes, the 1% increase in energy efficiency yields an additional 1.4% propensity for carbon reporting. Conversely, facing intense shareholder and activist pushback reduces disclosure probability by 1.6% and 0.5%, respectively.

Heterogeneity

Our analyses have focused on the average marginal effects of energy technologies on firm disclosure strategies and how stakeholders moderate this technology-disclosure relationship. It is, however, useful to know how these effects vary across different types of firms. For instance, different sectors face varying stakeholder pressures such that firms may react differently to regulatory and social pressures (Delgado-Márquez, Pedauga, and Cordón-Pozo, 2017). Such considerations also apply to the level of development (i.e. OECD vs. non-OECD) of firms' jurisdiction of operation. Furthermore, as high-performing and low-performing firms may behave differently in the face of stringent regulation and increased public pressure. For example, low-performing firms may be less likely to disclose their carbon impact whereas high-performing firms may be more willing to do so.

Hence, in Table 4, we re-estimate the baseline regressions separately for each sector (columns 1–3), as well as split-sample regressions across the level of development (OECD vs. non-OECD) in columns (4) and (5) and by firm performance (High vs. Low) in columns (6) and (7). For brevity, we present the overall effects on stakeholder variables only. The petroleum and industrial sector results generally mirror the sign patterns from the full sample results, albeit the stakeholder coefficients for the petroleum sector are larger in magnitude. However, we note that the shareholder effect in the industrial sector is not statistically significant. Specifically, the stakeholder effects in the petroleum sector suggest that stringent regulation generally incentivizes high-efficiency firms to report their carbon impact. In the Utilities sector results in column (3), the efficiency and regulation coefficients lose statistical significance with the activist coefficient retaining the negative sign albeit it attains statistical significance at only the 10% level.

The sign patterns of the stakeholder effects from the regional and performance regressions are also generally consistent with the baseline estimates. They show that regulation plays a role across the board for firms operating in OECD countries, irrespective of their efficiency levels. Conversely, the shareholder and activist effects are generally negative with some of the coefficients losing statistical significance or switching signs in the non-OECD sample (for activists) and the low-performing sample (for shareholders). The results suggest that activist pressures are negatively associated with carbon disclosure in non-OECD and low-performing countries, but we find no statistically significant relationship for the sample of high-performing firms. This finding is consistent with the

TABLE 4

Sectoral and regional regressions

	(1) *Sectors*	*(2)*	*(3)*	*(4)* *Regions*	*(5)*	*(6)* *Performance*	*(7)*
Dep. Var. Firm disclosed carbon	*Petroleum*	*Industrial*	*Utilities*	*OECD*	*Non-OECD*	*High*	*Low*
Overall effects							
TEF	0.2835***	0.3751***	0.2663***	0.9218***	−0.0934	0.2379***	−0.3881**
	(0.0831)	(0.0353)	(0.0889)	(0.0558)	(0.2536)	(0.0889)	(0.2499)
Regulation	0.0373***	0.0127***	0.0041	0.0225***	0.0294***	0.0123***	0.0218***
	(0.0070)	(0.0027)	(0.0093)	(0.0028)	(0.0066)	(0.0031)	(0.0044)
Shareholder	−0.0255	−0.0207	0.0758	−0.0015	−0.0104	−0.0308**	0.4021***
	(0.0193)	(0.0542)	(0.1081)	(0.0344)	(0.5898)	(0.0023)	(0.4764)
Activist	−0.0082***	−0.0024*	−0.0052**	0.0045**	−0.0030***	−0.0015	−0.0058***
	(0.0022)	(0.0013)	(0.0025)	(0.0023)	(0.0011)	(0.0017)	(0.0016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-specific time effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-specific time effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	−551.68	−2842.27	−542.62	−3311.91	−515.98	−2,594.63	−1,315.02
Pseudo R-squared	0.636	0.584	0.646	0.573	0.625	0.632	0.555
Firms	193	1174	180	998	549	1,295	774
Observations	2,742	16,594	2,576	13,763	8,149	14,378	7,534

Notes: This table contains the overall effects from probit regressions where the dependent variable in each regression is a dummy variable that takes the value of 1 when a firm discloses its carbon emissions in each period. The split-sample performance regressions are based on firm classifications using the median value of energy efficiency so that high-performing/low-performing firms are those with energy efficiency scores above/below the median value. All regressions include the controls employed in the baseline. Bootstrapped SEs in parentheses (100 replications).
* $P < 0.1$, **$P < 0.05$, *** $P < 0.01$.

notion that firm social responsibility dynamics are more responsive to activist pressures in less-developed countries (see Adetutu *et al.*, 2023).

An alternative measure of production technologies

So far, we have characterized the environmental performance of firm production technologies by the energy efficiency indicator. However, there may be concerns that the energy efficiency measure incorrectly captures the performance of firm-level production technologies. For example, firms may argue that, beyond the technical efficiency of a single (energy) input, they are instead motivated to improve their holistic performance across the entire production feasibility map. Hence, we check the sensitivity of our results by using an alternative but more comprehensive measure of firm production performance, namely TFP. In Table 5, we present the overall effects of the stakeholder variables, replacing the energy efficiency variable with productivity measures, namely TFP and the output to labour ratio. The TFP measures obtained from two different methods proposed by Levinsohn and Petrin (2003) (hereafter LP) and Ackerberg, Caves, and Frazer (2015)

TABLE 5

Estimation using TFP as measure of production technology

	(1) *Productivity method*	*(2)*	*(3)*
	LP-TFP	*ACF-TFP*	*Y/L*
Productivity	−0.0081***	0.0014	−0.0161***
	(0.0018)	(0.0025)	(0.0018)
Regulation	0.0170***	0.0172***	0.0168***
	(0.0022)	(0.0022)	(0.0024)
Shareholder	−0.0030	−0.0319*	−0.0146
	(0.0215)	(0.0163)	(0.0208)
Activist	−0.0080***	−0.0076***	−0.0082***
	(0.0010)	(0.0010)	(0.0008)
Firm effect	Yes	Yes	Yes
Year effect	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Sector-specific time effect	Yes	Yes	Yes
Country-specific time effect	Yes	Yes	Yes
Log-likelihood	−4,119.50	−4,124.95	−4,084.10
Pseudo R-squared	0.591	0.578	0.594
Firms	1,547	1,547	1,547
Observations	21,912	21,912	21,912

Notes: This table contains overall effects from probit regressions. The dependent variable in each regression is a dummy variable that takes the value of 1 when a firm discloses its carbon emissions in each period. All regressions include controls employed in the baseline. The LP method obtains TFP following the Levinsohn and Petrin (2003) procedure, while the ACF method follows the procedure proposed by Ackerberg *et al.* (2015). Y/L is the traditional measure of productivity measured as the ratio of firm output (Y) to number of employees (L). Bootstrapped SEs in parentheses (100 replications).
* $P < 0.1$, **$P < 0.05$, *** $P < 0.01$.

(hereafter ACF).[17] We find that the stakeholder effects retain their signs and qualitative implications from the baseline model but the shareholder effect either lacks statistical significance or is only significant at the 10% level.

Endogeneity

How sensitive are our estimates to the endogeneity of TEF and the stakeholder variables? In this sub-section, we address the endogeneity issues using IVs derived from global energy price shocks, colonists' environmental policy, the severity of natural disasters, and other firms' shareholder revolts. The instruments are jointly included in the first stage regression analysis.

Tables 6 and 7 present the second-stage IV-probit results and the first-stage OLS estimates, respectively. We first analyse the IVs using Table 7, which contains a regression of the endogenous regressors (i.e. TEF and the three stakeholder effects) on the instruments: oil and renewable energy (REN) prices for TEF, colonizer's environmental regulation (for regulation), natural disasters (for activism) and the total number of

[17] The ACF method is known to address the simultaneity bias arising from the potential correlation between firms' observable inputs and productivity estimates.

TABLE 6

Second-stage IV regression results

	(1)	(2)	(3)	(4)
TEF	0.382***	0.208***	0.214***	0.466***
	(0.026)	(0.015)	(0.004)	(0.016)
Regulation	0.014***			0.012***
	(0.002)			(0.000)
Shareholder		−0.015**		−0.015***
		(0.007)		(0.001)
Activist			−0.007***	−0.004***
			(0.001)	(0.000)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Sector time effect	Yes	Yes	Yes	Yes
Country time effect	Yes	Yes	Yes	Yes
Log-likelihood	39,750.43	33,378.73	81,254.22	−47,898.34
Firms	1,547	1,547	1,547	1,547
Observations	21,912	21,912	21,912	21,912

Notes: This table contains overall effects from the IV-probit regressions. The dependent variable in each regression is a dummy variable that takes the value of 1 when a firm discloses its carbon emissions in each period. All regressions include controls employed in the baseline. Bootstrapped SEs in parentheses (100 replications).
* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$.

TABLE 7

First-stage OLS regression

Endogenous regressor >>>>	*(1) TEF*	*(2) Regulation*	*(3) Activism*	*(4) Shareholders*
Oil price	0.006***			
	(0.000)			
REN price	−0.005***			
	(0.000)			
Colonist regulation		0.027***		
		(0.001)		
Natural disaster deaths			0.004***	
			(0.000)	
Other shareholder revolts				0.003***
				(0.001)
Controls	Yes	Yes	Yes	Yes
Kleibergen Paap F-test	74.81	25.68	64.31	11.02
Hansen J p-val	0.529	—	—	—
No of firms	1,547	1,547	1,547	1,547
Observations	21,912	21,912	21,912	21,912

Notes: This table reports the first-stage OLS estimates treating energy efficiency and the three stakeholder variables as endogenous. The dependent variables are the potentially endogenous variables namely TEF, Regulation, Activism, and Shareholder revolts in each period. The first-stage diagnostics, namely the F-test and Hansen-J statistics, are obtained from an analogous 2-SLS model. Bootstrapped SEs in parentheses (100 replications).
* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$.

shareholder activist campaigns relating to firms in other industries. In line with *a priori* expectations, the coefficients on the instruments have the expected signs, and they are statistically significant at the 1% level. Higher renewable energy prices increase energy efficiency performance. The first-stage Kleibergen–Paap F-stat of 74.81 far exceeds the suggested rule of thumb of 10 for the critical value. Furthermore, as anticipated by our arguments on instrumental relevance, the coefficients in columns 2–4 of Table 7 show that the other IVs have a positive relationship with the stakeholder variables.

In columns (1)–(3), we add the stakeholder interaction terms one at a time, and the results are qualitatively similar to the baseline findings. Column (4) presents the full model that simultaneously incorporates the three stakeholder interactions. The results in column 4 of Table 6 show that the three stakeholder interaction terms retain their sign properties and statistical significance. When compared to the baseline estimates in Table 3, the estimated TEF coefficient is larger in magnitude. However, the stakeholder coefficients are similar to the IV estimates in column 4, implying that the stakeholder variables have a smaller endogenity bias. The estimated effects in column (4) indicate a 1% increase in energy efficiency leads to a rise in the probability of carbon disclosure by 47% ($p < 1\%$), a larger effect than the 37% obtained in the baseline model. Furthermore, firms facing stringent regulatory regimes are 1.2% more likely to report carbon emissions. By contrast, operating under the shadow of intense shareholder and activist campaigns results in a 1.5% and 0.4% reduction in disclosure probability, respectively. Once again, these results are stable, leading us to conclude that our findings are robust to IVs analysis. To reiterate, these results are consistent with the notion that highly efficient firms have a higher propensity to report their carbon emissions when faced with more stringent environmental regulation, or less-intense shareholder and activist pushback against pollution.

Disclosure incentives

In a final piece of empirics, we conduct a basic analysis of the disclosure incentives of firms with superior environmental technologies. More specifically, we investigate the association between firm carbon disclosure behaviour in a given period and a range of publicly reported financial and sustainability metrics in the following year. Such analyses allow us to infer the returns for high-performing firms that adopt a disclosive strategy. We use the following model specification:

$$\text{Performance}_{it} = \alpha_i + \alpha_t + \beta_1 \text{Strategy}_{it-1} + \boldsymbol{\gamma} \boldsymbol{X}_{it} + \boldsymbol{\delta} \boldsymbol{X}_{ct} + \varepsilon_{it}, \quad (4)$$

where Performance_{it} refers to financial and sustainability measures such as profitability and energy reduction targets. Our independent variable of interest is the lagged Strategy_{it-1} which we derive as a time-varying indicator variable coded as 1 when a high-efficiency firm discloses its carbon impact and zero otherwise. We identify and denote 'high-efficiency' firms as those whose energy efficiency index fall in the top quartile of the efficiency distribution. α_i and α_t represent firm and time dummies, respectively. $\boldsymbol{X}_{it}$ and $\boldsymbol{X}_{ct}$ are firm-level and country-level controls used in our baseline analysis. Lagging the strategy variable intuitively allows us to capture the delayed response of the financial and sustainability metrics to disclosure decisions. The lagged values also allow us to mitigate any potential contemporaneous feedback effects. Yet, we do not make any claims about causality as our basic analysis only seeks to offer suggestive evidence on how firms' past disclosure behaviour is related to their future performance.

We present the results from this analysis in Table 8. In column 1, we use the traditional measure of firm profitability (i.e. net income). Given the prevalence of negative and zero profit values in the data sample, we use the inverse hyperbolic sine (IHS) transformation instead of the standard log transformation. This approach allows us to preserve the large data sample property of our analysis, rather than drop the zero values, while also offering a similar interpretation to estimates obtained from log-transformed data (McKenzie, 2017; Liu, Masulis, and Stanfield, 2021). However, given the limitations of the IHS transformation, we show an alternative profit regression based on the Poisson-Pseudo Maximum Likelihood (PPML) estimator. In column 3, we employ the return on asset (ROA) measure to enable us to adjust for firm size in profitability measurement.

We find that past carbon disclosure is negatively associated with both profitability measures. The result in column 1 suggests that disclosive firms are around 120% less profitable than their silent counterparts. This finding conveys an implicit financial penalty for environmental transparency that is economically and statically significant. Contrastingly, a disclosive strategy has a positive and statistically significant effect on the adoption of internal energy use targets and environmental management systems, as shown in columns 4 and 5, respectively. When taken together, these results suggest the trade-off implicit in the carbon reporting strategy of firms with strong environmental credentials: CSR-related sustainability benefits arise from carbon disclosure, but there is also a financial penalty for such disclosures. The financial penalty seems to be more

TABLE 8

Disclosure strategy and firm performance

Dep var. >>>>	*(1) Profit OLS*	*(2) Profit PPML*	*(3) ROA OLS*	*(4) Energy target OLS*	*(5) Env. management OLS*
Strategy_{it-1}	−1.292**	−0.333**	−0.010*	0.097***	0.109***
	(0.638)	(0.129)	(0.005)	(0.028)	(0.023)
Firm effects	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Sector time effect	Yes	Yes	Yes	Yes	Yes
Country time effect	Yes	Yes	Yes	Yes	Yes
R-squared	0.044	0.878	0.010	0.306	0.454
Observations	20,346	20,346	20,346	20,346	20,346

Notes: This table reports results of the effect of disclosive strategy on firm profitability and sustainability measures. Column 1 is the OLS regression based on the transformed profitability dependent using the inverse hyperbolic sine of net income, while column 2 employs Poisson-Pseudo Maximum Likelihood (PPML) estimator to account for the high incidence of zeros in the profitability variable. The measure in column 3 is represented by firm-level return on asset (ROA): the net income to total assets ratio. In column 4, the dependent variable is a dummy variable denoting whether a firm has an energy use reduction target, while column 5's dependent variable is a dummy denoting the presence of an in-house environmental management system and management team. SEs in parentheses are clustered at the firm level.
* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$.

than double the CSR benefit. These findings are also consistent with why some high-performing firms may adopt strategic silence in their approach to environmental reporting. Theoretically, studies (e.g. Lyon and Maxwell, 2011; Flammer *et al.*, 2021) suggest that firms can be hesitant to disclose their environmental credentials as such disclosures may be branded as 'greenwashing'[18] by activists and investors. Such potential accusations also seem consistent with the negative marginal effects on the two stakeholder interaction terms: TEF × Shareholder and TEF × Activist.

VII. Summary and conclusions

This paper has investigated the factors that shape carbon disclosure behaviour. In the absence of optimal incentive contracts for information extraction, we argued that energy-using and carbon-emitting firms would have mixed incentives for disclosure. Thus, the novelty of our approach relative to the extant literature is that we test the role of TEF as a determinant of firms' voluntary carbon disclosure decisions in the presence of stakeholder interventions. Moreover, an additional novelty of our study is that we exploit unique international firm-level panel data drawn from three micro datasets, namely the CDP, Thomson Reuters Refinitiv (Eikon API), and Boardex databases. Our multi-sector and multi-country panel data covers 1,547 firms across 24 countries from 2006 to 2020, allowing us to provide valuable empirical insight to inform the increasing global conversations on mandatory carbon reporting. Comparatively, few voluntary carbon disclosure studies, if any, go beyond the individual country or sector-level context. We tested a general framework in which firms chose whether to be energy efficient in their productive behaviour. We then relate their performance disclosure to market, shareholder and activist rewards and penalties, and regulatory stringency.

The paper used three empirical strategies to investigate the research question. We estimated potentially unobservable technical efficiency in energy use by employing the SFA approach to the production technology using the input distance function that caters to output endogeneity; we measured the likelihood of disclosure as a function of energy efficiency, regulatory stringency and shareholder and activist pressures using an endogeneity-adjusted probit model; and finally we related the firm's performance in both profitability and environmental management to its strategic choice about disclosure.

The results of the first estimation effort for production efficiency were robust, and we generated our energy efficiency scores from the IV estimation. In the second estimation strategy using a probit model of the likelihood of disclosure, our results show that higher energy efficiency technologies induce firms to disclose their carbon emissions, and we find robust evidence of the tendency of highly efficient firms to report their carbon emissions when operating in jurisdictions with more stringent environmental regulation. By contrast, such high-performing firms are less likely to disclose their carbon when operating in hostile conditions arising from intense environmental activism and shareholder campaigns. We paid close attention to potential endogeneity, using a two-stage IV probit model that upheld the robustness of our main findings. In addition, we find a positive association

[18] Other recent studies (e.g. Daubanes and Rochet, 2019; Adetutu *et al.*, 2023) document the rising intensity of such environmental campaigns in the context of the perceived laxity of environmental regulation.

between carbon disclosure and firm size, as well as executive board diversity and CEO quality.

Furthermore, we applied these robust findings to examine the consequences of firm disclosure strategy. We find that better-performing firms who report their carbon emissions demonstrated a propensity to perform well on sustainability metrics, but they recorded a financial penalty of a reduction in profitability by 120% relative to comparable firms adopting strategic silence.

This is a relatively new area of empirical investigation, and as we demonstrated the estimation issues can be complex. Our study sheds light on and promotes a more profound and robust understanding of the unexplored nexus between production technology heterogeneity, carbon disclosure and stakeholder pressures. The robustness of our finding that high energy efficiency reinforces the willingness to disclose but that shareholder and activist pressures are an obstacle to disclosure is clear. Given the rapid shift towards mandatory carbon disclosure, our paper offers timely implications for the future design of carbon disclosure schemes.

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Supporting Information

Additional Supporting Information may be found in the online Appendix:

Data S1. Supporting Information.

Data replication package: the data replication package is available at https://doi.org/10.3886/E188961