ISSN 2042-2695

CENTRE *for* ECONOMIC PERFORMANCE

CEP Discussion Paper No 1684

Revised November 2021
(Replaced March 2020 version)

Environmental preferences and technological choices: Is market competition clean or dirty?

Philippe Aghion
Roland Bénabou
Ralf Martin
Alexandra Roulet

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Economic and Social Research Council

Abstract
We investigate the effects of consumers' environmental concerns and market competition on firms' decisions to innovate in "clean" technologies. Agents care about their consumption and environmental footprint; firms pursue greener products to soften price competition. Acting as complements, these forces determine R&D, pollution, and welfare. We test the theory using panel data on patents by 7,060 automobile-sector firms in 25 countries, environmental willingness-to-pay, and competition. As predicted, exposure to prosocial attitudes fosters clean innovation, all the more so where competition is strong. Plausible increases in both together can spur it as much as a large fuel-price increase.

Key words: environment, product market competition, innovation

This paper was produced as part of the Centre's Growth Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

We are thankful for comments and suggestions from Ufuk Akcigit, Paul Goldsmith-Pinkham, Gene Grossman, Xavier Jaravel, Michal Kolesar, Eduardo Morales, Steve Redding, Jean Tirole, John Van Reenen, and from participants in the Institutions, Organizations and Growth (IOG) group at the Canadian Institute for advanced Research, at the EBRD Conference on "Environmental Economics and the Green Transition" and at the TSE workshop on "Markets, Morality and Social Responsibility". Léo Aparisi de Lannoy provided superb research assistance. Aghion and Bénabou gratefully acknowledge financial support from the Canadian Institute for Advanced Study, and Bénabou from the Innovation Lab at College de France as well.

Philippe Aghion, Collège de France, CIFAR, CEPR and Centre for Economic Performance, London School of Economics. Roland Bénabou, Princeton University, NBER, CEPR, CIFAR, Briq, ThreD, IZA and ERINN. Ralf Martin, Imperial College London and Centre for Economic Performance, London School of Economics. Alexandra Roulet, INSEAD and CEPR.

Published by
Centre for Economic Performance
London School of Economics and Political Science
Houghton Street
London WC2A 2AE

Should private firms get involved in mitigating climate change? A traditional view against such corporate activism is that firms should concentrate on maximizing profits, and let governments deal with externalities. In practice, however, we often see governments being ineffective at addressing environmental problems.[1] It then falls upon intrinsically motivated consumers, investors and firms to "do their part" through other channels.

This paper shows how citizens' social-responsibility concerns and the degree of competition between firms jointly shape the direction of innovation, acting as *complements.* We first develop a simple model of innovation where agents care about both the level and the environmental footprint of their consumption. We analyze how these "ethical" preferences, together with market structure, affect the equilibrium amount of clean R&D, and through it aggregate pollution and welfare.

While competition has a direct, short-run negative impact on the environment –lower prices induce more consumption and therefore more pollution[2]– it can also encourage clean innovation as a means of product differentiation. Intuitively, firms will seek to develop greener products when facing more environmentally motivated customers, and the more so, the harder they must compete for them.

Due to its offsetting quantity and quality effects, the impact of competition on emissions has a concave profile. Furthermore, because social responsibility and competition *leverage each other,* when the former is strong enough the profile can be hump-shaped, or even decreasing, reversing the direct effect. Similarly, more prosocial consumers not only push this profile down, but also make increases in competition (desirable for the usual reasons) less environmentally costly, or even beneficial.

We then bring together patent data, survey data on environmental values, and competition measures to test the model's key comparative statics. We relate the extent to which firms innovate in a clean direction to their exposure to pro-environmental attitudes and competition. Attitudes vary at the country level while competition is a Lerner-type index at the country times 4-digit sector level. A firm's exposure is defined as a weighted average of the country or country-sector level measures, where the weights proxy for the importance of the different countries to the firm. Our data covers

[1] Bénabou and Tirole (2010) discuss the sources of these limitations, and how they create a scope for individual and corporate social responsibility.

[2] The examples of China or India today, or the increasing market share of SUV everywhere since the 1980s, illustrate this. Similarly, increasing worldwide competition in the airline industry result in increasing travel and emissions.

7,060 firms and 25 countries during 1998-2002 and 2008-2012. We find a significant positive effect of pro-environment attitudes on the probability for a firm to innovate relatively more in the clean direction, and this effect is stronger, the higher competition is. Our empirical analysis suggests that the combination of realistic increases in prosocial attitudes and in product market competition can have the same effect on green innovation as a 17% increase in fuel prices worldwide.

Our research contributes to several literatures. The first one is that on competition and innovation (Aghion et al., 1997, 2001, 2005; Vives, 2008). The second is that on growth and the environment pioneered by Nordhaus (1994) [3], particularly the work on endogenous directed technical change analyzing how R&D is shaped by public policies such as carbon taxes and/or subsidies to green innovation (Newell et al., 1999; Popp, 2002; Acemoglu et al., 2012; Aghion et al., 2016). We connect these two literatures and bring in individuals' willingness to "do their part" through their own consumption choices, which becomes essential when policy-making is deficient. Third is the literature on individual and corporate social responsibility (CSR), both reflecting a mix of intrinsic and reputational motivations (Bénabou and Tirole, 2010, 2011; Hart and Zingales, 2017); we introduce here product competition as a channel through which consumers' social preferences influence firms' investment decisions. This also relates the paper to experiments such as Falk and Szech (2013) and especially Bartling et al. (2015), where lab subjects compete in the roles of both consumers and producers.

On the empirical side, some papers have examined how competition affects CSR performance, finding mixed results.[4] We depart from this literature in several ways. First, we focus on the environmental dimension rather than overall CSR, on the automobile industry, and on firms' innovation decisions rather than their production or emissions (which, the model shows, need not go in the same direction). Most importantly, we emphasize the *interaction,* in each firm's set of markets, between competition and consumers' environmental concerns. Differences in national preferences and firms' differential exposures to them not only have a significant effect *per se*, but turn out to be what makes competition actually matter for whether R&D is clean or dirty.

[3] See also Nordhaus (2002), Stern (2007) and Weitzman (2007, 2009)

[4] See Fisman et al. (2006) Fernández-Kranz and Santaló (2010), Flammer (2015), Hawn and Kang (2013), Duanmu et al. (2018), and Liu et al. (2021).

I. Model

Time is discrete, with individuals and firms living for one period. At the beginning of each period t, firms choose R&D investments, aiming to maximize expected profits. Once innovations have realized, firms produce with their respective technologies, competing for consumers. Revenues are paid out as wages to production and R&D workers, and net profits are redistributed to consumers, who are also firms' shareholders.

A. Preferences

There is a continuum of differentiated goods, $j \in [0, 1]$. Within and/or across these sectors, firms potentially differ both by the price they charge and the environmental (un)friendliness of the goods they produce. The production or consumption of one unit of good with environmental quality q generates $x = 1/q$ units of polluting emissions.

The representative consumer has standard taste-for-variety preferences, but is also concerned about his environmental footprint. When buying $y_{j,f}$ units of quality $q_{j,f}$ from each firm f in sector j (denote that set as $\mathscr{F}_j$) , he achieves consumption utility

$$U_t = \int_0^1 \ln \bar{y}_{j,t}\, dj, \tag{1}$$

where

$$\bar{y}_j = \int_{f \in \mathscr{F}_j} y_{j,f} \ \ (q_{j,f})^{\delta}\, df \tag{2}$$

is his emissions-impact-discounted consumption of variety j. The disutility suffered from total emissions will come in subtraction when analyzing welfare, but is taken by each individual as given.

These preferences embody a form of ethical motivation. An individual's contribution to aggregate emissions is negligible, and for instance does not affect the quality of the air anyone breathes; nonetheless, he intrinsically dislikes contributing to the externality. He feels guilty, or/and socially embarrassed, about the carbon he emits when driving or flying, and so would pay a premium for cleaner goods. δ captures the strength of these social-responsibility concerns.

While sectors are imperfect substitutes, within each one firms' quality-adjusted offerings are perfect substitutes. Therefore, all demand for variety j will go to the firm(s) in $\mathscr{F}_j$ with the highest quality/price ratio, q^δ/p. Furthermore, with logarithmic preferences the same amount will be spent on each variety; we normalize it to 1, choosing current expenditure as the numeraire.

B. Technology and market structure

Labor is the only input, with agents offering an infinitely elastic supply at a wage normalized to 1. It takes c units of labor to produce one unit of output (e.g., one car), with the firm's technology determining the associated emissions, $1/q$. That technology, in turn, reflects the cumulative number $k_f \in \mathbb{N}$ of (green) innovations it made in the past, or copied from someone who did:

$$q_f = \gamma^{k_f},$$

where $\gamma > 1$ measures the size of a leading-edge environmental innovation. Since consumers value a quantity-quality combination (y, q) as yq^δ, it effectively takes $c\gamma^{-\delta k_f}$ units of labor for a firm at level k_f to produce one unit of quality-adjusted output.

Each sector j consists of a duopoly, $f = A, B$, plus a lagging competitive fringe, as follows. First, in each period t both firms have free access to the frontier technology achieved in period $t-1$. These strong knowledge spillovers simplify the R&D problem, by limiting the investment horizon to a single period.

Second, a firm's R&D effort can result in at most one innovation over the current frontier: for any $z \leq 1$, investing $\kappa z^2/2$ units of labor yields a probability z of inventing a technology that is γ times cleaner, and a probability $1 - z$ of zero progress.

Together, these assumptions imply that the gap that can open between firms is at most one innovation, $|k_B - k_A| \in \{0, 1\}$, and it *resets to zero* at the start of every period.

A third simplifying assumption is that, at the innovation stage (where $k_A = k_B$), only one (either) of the two firms has an opportunity to invest in R&D. The other lacks, in the current period, a suitable idea or managerial capacity, effectively making its κ prohibitively large.

There can thus, at any point in time, only be two kinds of sectors: *leveled*, where the duopolists' qualities are "neck-and-neck", and *unleveled*, where a *leader* is one step ahead of its *follower*. At the start of each period t, which corresponds to the *investment* phase, all sectors are neck and neck, while during the subsequent *production* phase of that period, a fraction z are unleveled, corresponding to the R&D intensity chosen by investing firms.

In each sector, there is also a competitive fringe of potential entrants. These firms will neither produce nor do research in equilibrium but act as a threat, disciplining the duopolists. We thus assume that, at the start of each period t, the fringe can costlessly imitate the previous-best technology, meaning one that embodies only the $k' = k - 1$ previous innovations, where $k = k_A = k_B$ is the level from which the duopolists start, and may further innovate.

C. Competition and profits

Recall that consumers spend the same amount on each variety, and firms in each sector compete for that fixed revenue, normalized to 1. Consider first an unleveled sector, where an innovation just occurred. The leader has a quality advantage of γ^δ over the follower –its cars pollute γ times less– so it can engage in limit pricing, charging $p_M = \gamma^\delta c$ and capturing all demand. The output and operating profits of such a *de facto* monopolist are

$$y_M = \frac{1}{p_M} = \frac{1}{\gamma^\delta c}, \quad \pi_M = 1 - \frac{1}{\gamma^\delta}. \tag{3}$$

Consider now a leveled sector, where no innovation recently occurred. If the two firms engage in unfettered competition the equilibrium price falls to c, resulting in zero profits. Conversely, if they collude perfectly to maximize joint profits, they set $p = p_M$ like the leader in an unleveled sector, and reap $\pi_M/2$ each. Indeed, $c\gamma^\delta$ is the price that just keeps out the competitive fringe, which produces goods γ times more polluting than those of the duopolists.

Following Aghion et al. (2005), we span the range between these two extremes by representing (inverse) market competition as the extent to which neck-and-neck firms are able to collude at the production-and-sales stage. Thus, we assume that the normalized profit for each firm is:

$$\pi_D(\Delta) \equiv (1 - \Delta)\,\pi_M,$$

where $\Delta \in [1/2, 1]$ parametrizes the degree of competition.[5] The corresponding price and sectoral output are given by equating total profits to total sales minus costs:

[5] We assume that collusion occurs only at the (ex-post) stage of production and pricing, and not at the ex-ante stage of R&D, which for instance could be harder to monitor.

$$(4) \qquad p(\Delta) = \frac{c}{1-2(1-\Delta)\pi_M} = \frac{c}{1-2(1-\Delta)(1-\gamma^{-\delta})} \in [c, p_M],$$

$$(5) \qquad y(\Delta) = \frac{1}{p(\Delta)} = \frac{1}{c}\left[1-2(1-\Delta)(1-\gamma^{-\delta})\right] \in \left[y_M, \frac{1}{c}\right].$$

For given technologies, competition has the standard effect of forcing down the equilibrium price, which increases consumer demand and production. More units produced and sold, in turn, result in more emissions –the *mass-consumption effect*. The other consequence of competition is to affect incentives to innovate, which we examine next.

D. Escaping competition through clean innovation

Recall that each sector starts the current period with both firms neck and neck, then one of the two (at random) is endowed with an opportunity for engaging in R&D. If it invests $z \leq 1$, it succeeds in developing a cleaner technology with probability z, reaping π_M; with probability $1-z$ it fails and must collude with its equally able competitor, reaping only π_D. A potential innovator thus solves

$$\max_{z\in[0,1]} \left\{ z\pi_M + (1-z)\,\pi_D(\Delta) - \kappa z^2/2 \right\},$$

resulting in $z = \min\left\{(\pi_M - \pi_D(\Delta))/\kappa, 1\right\}$. We restrict attention to parameters values such that

$$(6) \qquad \kappa > \pi_M = 1 - \frac{1}{\gamma^{\delta}} \equiv \kappa_1,$$

meaning that innovations are not too easy in terms of their importance or cost. The optimal R&D intensity is then interior,

$$(7) \qquad z(\Delta) = \frac{\Delta \pi_M}{\kappa} = \frac{\Delta}{\kappa}\left(1 - \frac{1}{\gamma^{\delta}}\right).$$

Averaging across sectors $j \in [0,1]$, the rate of R&D is also the proportion of them where innovation will occur, so the aggregate flow of clean innovations per period is simply $I \equiv z(\Delta)$. Hence:

Proposition 1. *Both market competition and consumers' social-responsibility concerns raise investment in, and the total flow of, clean innovations. Moreover, these two forces* *act as complements:*

$$\frac{\partial I}{\partial \Delta} > 0,\ \frac{\partial I}{\partial \delta} > 0,\ \frac{\partial^2 I}{\partial \Delta \partial \delta} > 0. \tag{8}$$

In a more general model with clean *and* dirty innovations (e.g., SUV's), greater competition would generally enhance both types, but the proportion of clean ones would still rise with prosocial values and their interaction with market competition.

E. Pollution and Welfare

At the production stage of each period, there is a fraction z of sectors in which one firm has become cleaner than the other by a factor γ, and a fraction $1-z$ where the innovation effort has failed, so that both still use period $t-1$'s frontier technology. Total emissions (normalized by total expenditure) thus equal:

$$X = [1 - z(\Delta)]\, y(\Delta) + z(\Delta) y_M / \gamma. \tag{9}$$

This is a concave quadratic polynomial in Δ, reflecting two opposing effects. On the one hand, by increasing output $y(\Delta)$ in neck-and-neck sectors, competition directly increases pollution. On the other hand, the fear of lower profits causes firms to seek a quality advantage through R&D; as a result, a greater fraction $z(\Delta)$ of sectors develop clean technologies, which tends to reduce emissions.

Proposition 2. *Define* $\kappa_2 \equiv 1 - \gamma^{-\delta}\left(1 + 1/\gamma\right)/2 > \kappa_1$ *and let* $\kappa > \kappa_1$*. As competition* $\Delta \in [1/2, 1]$ *increases:*
(a) for $\kappa < \kappa_2 - \kappa_1/2$*, aggregate pollution* $X(\Delta)$ *decreases monotonically;*
(b) for $\kappa > \kappa_2 + \kappa_1/2$*,* $X(\Delta)$ *increases monotonically;*
(c) for $\kappa \in (\kappa_2 - \kappa_1/2, \kappa_2 + \kappa_1/2)$*,* $X(\Delta)$ *is hump-shaped; moreover, it is minimized at* $\Delta = 1$ *(versus* $\Delta = 1/2$*) if and only if* $\kappa < \kappa_2$*;*
(d) for all κ *in* $[\kappa_1, \kappa_2]$*,* $X(\Delta)$ *is minimized at* $\Delta = 1$[6]*.*

This proposition and the next are illustrated in Figure 1. All propositions are proved in Appendix A.

[6]Proof outline. The polynomial (9) is maximized at $\hat{\Delta}_X(\kappa,\gamma,\delta) = 1/2 + \left(2\kappa - 1 + \gamma^{-\delta}/\gamma\right)/4\pi_M$, which rises with κ from $1/2$ at $\kappa_2 - \kappa_1/2$ to 1 at $\kappa_2 - \kappa_1/2$. Moreover, $X(1) < X(1/2)$ if and only if $\kappa_1 < \kappa_2$.

Proposition 3. *Aggregate pollution $X(\Delta)$ decreases with consumers' social-responsibility concerns δ. For all $\kappa > \kappa_1$ (more generally, if R&D effort is interior) it decreases more the stronger is market competition: $\partial^2 X / \partial\Delta\partial\delta < 0$.* [7]

Let us now evaluate net social welfare. Its first component is utility from consuming the z "greener" and the $1 - z$ "dirtier" varieties,

$$U = (1 - z(\Delta)) \ln y(\Delta) + z(\Delta) \ln[\gamma^\delta y_M]. \tag{10}$$

Competition raises U through both a quantity effect (higher $y(\Delta)$) and a quality effect (higher $z(\Delta)$, reallocating consumption toward cleaner varieties). The second component of wellbeing is environmental quality. Assuming a linear disutility from aggregate pollution, welfare equals[8]

$$W = U - \psi X, \ \psi > 0. \tag{11}$$

Proposition 2 showed that, when innovation costs κ are relatively high, or competition Δ relatively weak, $\partial X / \partial \Delta > 0$. Whether greater competition improves or damages social welfare then hinges on how large ψ is. When κ is low and Δ sufficiently high, conversely, $\partial X / \partial \Delta < 0$, so $\partial W / \partial \Delta > 0$.

The impact of prosocial concerns similarly depends on how costly R&D is, and on the competitive pressure on firms to bear those costs. For fixed z, a higher δ means that consumers experience more "guilt" from each unit of pollution embodied in their consumption, lowering U. A more environmentally responsible population, however, pushes firms to produce cleaner goods: z increases, raising U and lowering X.

Proposition 4. *(a) For $\kappa \in [\kappa_1, \kappa_2 - \kappa_1/2]$, social welfare W increases monotonically with competition; more generally, there is $\widehat{\kappa} > \kappa_2$ such that, for all $\kappa \in [\kappa_1, \hat{\kappa}]$, W is maximized at $\Delta = 1$; (b) W increases with consumers' environmental concerns δ if and only if competition is strong enough. (c) If ψ is large enough or if $\kappa \geq 2\kappa_1$, preferences*

[7] Proof outline. (a) In (9), as δ rises, both y_M and $y(\Delta)$ decrease (agents reduce their consumption to pollute less), and there is a substitution towards cleaner goods ($z(\Delta)$ rises). (b) The higher is Δ, the less responsive is $y(\Delta)$ to consumer preferences (as profits $\pi(\Delta)$ declines), whereas z responds more.

[8] These are the only two terms, since: (i) the disutility of labor employed in production and research is exactly compensated by wage payments; (ii) wages plus operating profits are entirely consumed by individuals, so that total income equals total spending.

and competition are complements, $\partial^2 W/\partial\Delta\partial\delta > 0$. [9]

II. Empirical strategy and identification

We now test the model's key predictions for innovation, stated in Proposition 1. Specifically, we relate the extent to which a firm increases its innovation in the clean direction to changes in its exposure to environmental values and competition, by running regressions of the form:

$$\begin{aligned}\Delta Innovation_j = \alpha\Delta Values_j + \beta\Delta Competition_j + \gamma\Delta(Values_j \times Competition_j)\\ + \delta\Delta X_j + \varepsilon_j.\end{aligned} \tag{12}$$

All variables are first differences at the firm level between 2008-2012 and 1998-2002. We restrict the analysis to these two periods because of data constraints (see below). In our preferred specification, $Innovation_j =$ log(1+number of clean $patents_j$)- log(1+number of dirty $patents_j$).[10]

$\Delta Values_j$ is a firm-specific weighted average of country-level changes in pro-environmental attitudes:

$$\Delta Values_j = \sum_{c=1}^{25} \omega_{j,c} \times \Delta values_c,$$

where $\omega_{j,c}$ measures the importance of country c for firm j. In theory one would use firms' sales or profits, but such data is not available. Instead, we compute $\omega_{j,c}$ using the share of patents filed in country c by firm j between 1950 and 1995, based on the idea that protecting intellectual property is more worthwhile where one expects its market to be larger. Aghion et al. (2016) show that these weights are very correlated with sales for the firms for which country-level sales data is available. We restrict attention to the 25 countries for which we have data on both environmental values and potential confounders (i.e. fuel price and environmental policies). Our competition measure is also a shift-share variable described below. Finally, the X_j are controls defined below.

[9]Proof outline. Given the properties of $X(\Delta)$ in Proposition 2: (a) follows from $\partial U/\partial\Delta > 0$ and (b) from the fact $\partial U/\partial\pi_M > 0$ when Δ is above some threshold $\underline{\Delta}\ (\pi_M, \kappa)$ that makes the product mix $z(\Delta) = \Delta\pi_M/\kappa$ sufficiently responsive to $\pi_M = 1 - \gamma^{-\delta}$ to dominate the increased guilt from consumption (discussed above), as δ rises; (c) follows directly from (11) where ψ is concerned; for κ, it follows from (10) and (4).

[10]We show robustness to using clean share defined as $\frac{(1+clean_j)}{(2+clean_j+dirty_j)}$. The 1 added to both numerator and denominator ensures smoothness for firms who did not patent in one of the periods.

The shift share or Bartik design used for our main variables of interest has recently been discussed by Goldsmith-Pinkham et al. (2020); Borusyak et al. (forthcoming) and Adão et al. (2019). These suggest two paths to identification: exogenous shocks and exogenous weights. A possible threat to identification in our setting is that firms with higher capabilities to innovate in clean technologies might patent more in countries with more pro-environmental consumers. This would introduce endogeneity with respect to both shocks and weights. Additionally, the innovation behaviour of national champions might exert a direct influence on country-level values.

We take several steps to address such concerns. First, our regressions are in first differences between our two periods. Second, the weights are based on pre-sample patenting behaviour. Hence, we only require firms' clean innovation *growth* (rather than *level*) to be unrelated to country-level shocks and/or to market selection in the pre-sample period. Third, we control for the headquarter country, which deals with reverse causality due to support for "national champions".

Fourth, our preferred specification includes extensive conditioning variables: dummies for the country with the maximum weight for every firm; sector dummies to purge any potential endogeneity arising from sector-specific growth shocks; and variables using the same firm country weights (population, GDP, fuel price, environmental policies index) to control for potential country-level confounders correlated with the dependent variable and the shocks of interest.

Besides identification issues, Adão et al. (2019) also note that common country-level shocks across firms with a similar weight structure can affect standard errors. We consequently perform the adjustment proposed by Adão et al. (2019), noting that because our framework includes interactions effects and many controls, it lies somewhat outside the set of formal results available in their paper (see Appendix D for details).

III. Data

A. Innovation

Our innovation measures come from patents in the car industry. Compared to R&D investment, patents are available at a more disaggregated level, and can thus be classified as clean or dirty. Moreover, the auto sector is innovation-intensive and patents are perceived as an effective means of protection against imitation, something not true in all sectors (Cohen et al., 2000). An innovation is typically patented in multiple countries, but the European Patent Office's PATSTAT database allows us to track all individual patents belonging to the same family. A patent family identifies an inventive step that is subsequently patented several times with different patent offices. We use this to count families rather than patents, and refer to a family as an innovation.

To classify innovations, we use the International Patent Classification system (IPC) and the Y02 classification introduced by the European Patent Office in 2002 to rate the climate impact of innovations (both pre- and post-2002). Clean innovations are those involving non-fossil-fuel-based propulsion, such as electric or hydrogen cars and affiliated technologies (e.g. batteries), while dirty ones are those related to the internal-combustion engine (ICE). We leave aside the "grey" and "other" categories, which are neither unambiguously "clean " nor "dirty" (see Table C.1).

Figure 2 shows the worldwide evolution of car-related innovations since the 1960s. The annual number has grown from around 3,000 in the 1960s to over 40,000 in 2010. Until 2000, this growth was mostly driven by patents in the "other" category, but since then clean patents also grew rapidly. Our sample consists of all firms in the industry that patented at least once during either 1998-2002 or 2008-2012[11] and for which we have the 4-digit sector code, required for our competition measure. This yields 7,060 firms, of which 2,662 patented in both periods. In 1998-2002, conditional on patenting, the average number of innovations per firm is 0.78 clean ones and 4.3 dirty ones; in 2008-2012, these figures are 3.2 for both types.

B. Environmental values

The data on attitudes comes from the International Social Survey Program (ISSP) and the World Value Survey (WVS). Several questions could capture the values we are interested in, but they are often asked only in a limited set of countries or during a single survey wave. We thus create a synthetic index based on i) the only question common to both surveys that asks about willingness to accept higher taxes for the environment and ii), since taxes pertain to public policy more directly than to consumer spending, one additional question from each survey. In the ISSP it is about willingness to pay higher

[11] Our environmental willingness-to-pay measures are available only during these two periods. We thus take five-year windows centered on 2000 and 2010, and sum a firm's annual innovations over each.

prices in order to protect the environment, and in the WVS it is about willingness to give up part of one's income to prevent environmental pollution.

We code all answers so that higher values mean more pro-environmental attitudes (see Appendix C for details). We then average all variables at the country-period level, transform them into z-scores, and eventually average across all variables available for the country-period observation. We thus have data on environmental willingness-to-pay for 25 countries for 2 periods, namely 2000 and 2010.

In most countries, pro-environmental values decreased over this period. This is not a specificity of the datasets we use, nor of the exact point in time when we measure attitudes. Appendix B Figure A1 provides a time-series plot of answers to a similar question, asked by the Gallup survey (Gallup, 2019) to US respondents. The prevailing trend from the early 1990s to the beginning of the 2010s was a sharp *reduction* in environmental concerns. The reasons for this are unclear, and there is even little awareness of this fact in the literature. Figure A1 also shows a sharp reversal after our period of analysis. This is a more general trend: Carlsson et al. (2021) show that between 2010 and 2020 willingness to pay for climate mitigation increased also in China and Sweden. Therefore, in the last section, we will forecast what our estimates imply for green innovation if the decrease in environmental values during the first decade of the 2000s was totally erased by their more recent upturn.

C. Competition

To compute a firm's exposure to competition, we rely on a Lerner-Index-style approach, derived from a structural production-function regression. This requires using additional balance-sheet data from ORBIS. Compared to a standard Lerner Index, it allows for non-constant returns to scale and quasi-fixed production factors (see Appendix C.3). Contrary to other sectors, or national trends, most automobile firms experienced a reduction in market power during that time period (see Appendix, Figure A2).

A Lerner-style competition measure, however, raises endogeneity concerns. Patents, by definition, give the holder market power, so if we find a relation between competition and innovation it could be due to reverse causality. We therefore assume that firm-level competition at time t (inverse markups) is a weighted average of the degree of competition in country c and 2-digit sector s, $comp_{c,s(j),t}$ and an idiosyncratic firm-level shock $\nu_{j,t}$:

$$\frac{1}{\mu_{j,t}} = \sum_c comp_{c,s(j),t} \times w_{c,j} + \nu_{j,t}.$$

Rather than use raw inverse markups, one would like to base the analysis on the $comp_{c,s(j),t}$, which are not directly observed. In principle, we could recover the $comp_{c,s(j),t}$ by regressing (inverse) markups on patent weights $w_{c,j}$, but weights might again be endogenous to firm-level shocks. We therefore base our assessment of the market environment for firm j on firms other than j, specifically on firms outside of j's narrow 4-digit industrial sector. Indeed, if a close competitor to j succeeds with an innovation, it could reduce j's markup or affect its patent shares (j may try to differentiate itself by focusing on other countries). Our "leave-one-sector-out" instrument assumes that a firm's innovation would only causally affect firms within its narrow sector, but not outside.[12]

D. Country-level controls

We control for end-user, tax-inclusive automotive fuel prices from the International Energy Agency (IEA), real GDP per capita from the World Bank, population from the IMF's World Economic Outlook, and the Environmental Policy Stringency (EPS) Index from the OECD, which provides a comprehensive measure of environment-related regulations, taxes, tariffs, and R&D subsidies. All country-level indicators are transformed into firm-level variables through the same weighting approach as for the main regressors.

E. Patent portfolio weights

Our benchmark definition of country-firm weights $\omega_{j,c}$ is the share of a firm's patents filed in each country between 1950 and 1990. We include all patents of the firm in the relevant countries, not only automobile-related ones. Germany and the US have the

[12] We compute our firm-level competition index by first running, for each firm j, a regression $\frac{1}{\mu_{i,t}} = \sum_c comp_{c,s(i),t} \times w_{c,i} + \nu_{i,t}$ on the sample of firms i such that $s(i) = s(j)$ and $s4dig(i) \neq s4dig(j)$, where $s4dig(i)$ is the 4-digit sector classification of firm i. This provides us with firm-specific estimates $\hat{comp}_{c,s(j),t}$ of the competitive environment for every country and time period. Provided the shocks to ε_j in (12) only affect firms within a 4-digit sector, these estimates will be orthogonal to them. Our index of exogenous changes in firm-level exposure to competition is therefore $\Delta \hat{comp}_j = \sum_c \left(\hat{comp}_{c,s(j),t} - \hat{comp}_{c,s(j),t-1} \right) w_{c,j}$. Appendix C.4 provides more details.

largest weight, with 8% on average, followed by the UK, France, Korea and Japan, with about 4% on average. Other weights definitions yield similar results.

IV. Empirical results

Table 1 reports our benchmark results, with all magnitudes expressed as z-scores. Panel A displays the main effects of environmental values, competition and their interaction on the direction of innovation, controlling only for population and GDP per capita. Panel B further controls for fuel price and environmental policies. Panel C adds sector fixed effects and dummies for the headquarter country and that with the highest weight. Column 1 shows the main outcome of interest, namely the change in the growth rate of clean innovations relative to dirty ones; Columns 2 and 3 report the effects on both types separately, while Column 4 uses the change in the share of clean patents, to alleviate potential concerns related to the log transformation.

We see that greener consumer values significantly push innovation in the clean direction, and all the more so where competition is high. Competition has a positive effect on clean innovation, but it is not significant once we add all the controls (panel C) [13].

In our preferred specification of panel C, a one-standard-deviation increase in exposure to pro-environmental values is associated with a growth rate of clean patents 16% higher than that of dirty ones, at the mean level of competition. This effect increases to 20% for levels of competition one standard deviation higher than the mean. Predictably, an increase in fuel prices is also associated with a higher growth rate of clean patents relative to dirty ones.

Table 2 examines the results' robustness, using as benchmark the specification of Table 1 Panel C. Panel A incorporates pre-period GDP into the weights definition, based on

[13] This is consistent with the model, for small δ : $z(\Delta) \approx (\Delta/\kappa)\delta \ln \gamma$, so $\partial z/\partial \Delta \approx 0$ whereas $\partial z/\partial \delta$ and $\partial^2 z/\partial \delta \partial \Delta$ are significantly positive. More generally, the net effect of competition on R&D is known to be ambiguous (see the introduction), and our estimates suggest that environmentally conscious consumers help tilt that balance towards more (clean) innovation.

the idea that large countries matter more[14] [15]:

$$\omega_{j,c} = \frac{\omega_{j,c} \times GDP^{.35}_{c,pre-period}}{\sum_{c=1}^{25} \omega_{j,c} \times GDP^{.35}_{c,pre-period}}. \tag{13}$$

Panel B performs the analysis at the firm-country level, for which no weights are needed. The specification is:

$$\begin{aligned} \Delta Innovation_{j,c} &= \alpha \Delta Values_c + \beta \Delta Competition_c + \gamma \Delta Values_c \times Competition_c \\ &\quad + \delta \Delta X_c + \varepsilon_{j,c}. \end{aligned} \tag{14}$$

In the firm-level analysis, if an innovation is patented in several countries we count it once and use the date of the first patent. Here, we look at all patents: for a given innovation, there might be different filing dates for different countries.

Panel C reports the standards errors computed using Adão et al. (2019)'s formula. This adjustment is not straightforward, as our setting features an interaction term between two shift-share variables, as well as many controls. In our case, this leads to lower standard errors. This suggests negative correlation of the residuals within cluster (where cluster refers here to the weighted exposure to countries)[16].

To summarize: in line with the model's predictions, pro-environmental values push innovation in the clean direction, all the more so when competition is more vigorous.

1 V. Accounting and counterfactual exercises

We now use our fitted model (Table 1, Panel C) to conduct both retrospective and prospective simulations.

[14] Following Dechezleprêtre et al. (2019), we use $(GDP)^{.35}$: Eaton et al. (2011) estimate an elasticity of firms' average exports to GDP of destination country of 0.35

[15] Further checks are available upon request. In particular, some firms in our sample did not patent in the relevant set of countries during the pre-period. In our baseline specification, we assign them uniform weights, by adding 1 to the number of patents of a firm in each country. This ensures a smooth transition between firms with and without pre-sample patents. Our results are robust to i) not doing this transformation, ii) dropping firms that did not patent in the pre-period, iii) assigning them, for each country, the average weight among firms that *did* patent in the pre-period.

[16] In specifications without any control, the adjustment increases standard errors relative to the benchmark but the coefficients of interest remain significant; we do not report it because the point estimates are not well identified without controlling for potential confounders.

Table 3 (Panel A, Column 1) shows that, between 1998-2002 and 2008-2012, the share of clean innovations increased by 35 percentage points. How can this be reconciled with the fact that citizens in our sample countries generally became *less* concerned with environmental priorities between 2000 and 2010?

First, environmental attitudes evolved very differently across countries. If the only change had been a uniform decline (the observed mean), the clean share would have fallen by 4.8 percentage points. Because of correlation between firms' changes in exposure ΔV_j and their level of patenting activity (see Appendix B for details), the impact of the properly weighted average of ΔV_j's is somewhat different, but still adverse: evaluated at the (patent-weighted) average level of competition $\bar{C}$, it equals -1.9 points (Column 2). This negative effect is further reversed because values decreased more for firms exposed to lower levels of competition (Column 3). Columns 4 and 5 consider the same decomposition for competition. The effect of competition is close to zero (the coefficient for competition in Table 1 Panel C is almost zero). The pure interaction effect is small due to values and competition moving in opposite directions on average (Column 6). Hence, on net, competition and value changes account for a small negative change in clean shares of -1.1 percentage points (Column 7).

Second, over that period there was a doubling of tax-inclusive fuel prices. Column 8 shows that incorporating variations in oil prices explains 20.2 percentage points, almost 2/3 of the observed clean share. The rest is mostly explained by changes in environmental policies (our EPS variable is included in Column 9 "Other").

In Panel B we turn to a *prospective* scenario, asking what would happen if –starting from the 2008-2012 values– there was an increase in both competition and prosocial attitudes. To simulate realistic magnitudes, we use the average *absolute* changes seen between Period 1 and 2. For values, there was a decrease of 0.78 standard deviations, and we now simulate a *uniform* increase of the same size; for competition there was an increase of 0.08 standard deviations, and we consider a same-sized uniform increase.

We find that the envisioned increase in prosocial attitudes would raise the share of clean innovations by $4.4 + 0.8 = 5.2$ points, while that in competition would have an effect close to zero. Their combined effect is a 5.4 points increase, which is equivalent to that of a 17% world-wide rise in fuel prices. Given that even moderate attempts to increase fuel prices often elicit dramatic public reactions (e.g. the French "Gilet Jaunes") or political gridlock (e.g. the US Congress), this suggests that grassroots and public campaigns to promote citizens' environmental responsibility could be a viable alternative policy option, especially where markets can be expected to become more competitive.

VI. Conclusion

Are citizens' often-stated desires to adopt more environmentally responsible behaviors just "cheap talk", or powerful motivations that end up having a major influence on what new products will be developed and sold? And what is the role of market competition in the process? To answer these questions, we proposed a simple model and brought together data on firm-level automotive-sector patents, national environmental attitudes, and competition intensity. We found support for the predictions that pro-environment attitudes and its interaction with competition both have a significantly positive effect on the probability for a firm to aim at cleaner patents.

More generally, the results provide support for models in which intrinsically or reputationally motivated individuals incur costs to act in a "socially responsible" manner in spite of having a negligible impact on the aggregate outcome, such as pollution. Moreover such prosocial motivations can actually "move markets", even at the upstream stage of product research and development, especially if competition can be expected to intensify.

References

D. Acemoglu, P. Aghion, L. Bursztyn, and D. Hemous. The Environment and Directed Technical Change. *American Economic Review*, 102(1):131–166, Feb. 2012.

R. Adão, M. Kolesár, and E. Morales. Shift-Share Designs: Theory and Inference*. *The Quarterly Journal of Economics*, 134(4):1949–2010, 08 2019.

P. Aghion, C. Harris, and J. Vickers. Competition and growth with step-by-step innovation: An example. *European Economic Review*, 41(3):771 – 782, 1997. Paper and Proceedings of the Eleventh Annual Congress of the European Economic Association.

P. Aghion, C. Harris, P. Howitt, and J. Vickers. Competition, Imitation and Growth with Step-by-Step Innovation. *The Review of Economic Studies*, 68(3):467–492, 2001. Publisher: [Oxford University Press, Review of Economic Studies, Ltd.].

P. Aghion, N. Bloom, R. Blundell, R. Griffith, and P. Howitt. Competition and Innovation: an Inverted-U Relationship. *The Quarterly Journal of Economics*, 120(2): 701–728, May 2005. Publisher: Oxford Academic.

P. Aghion, A. Dechezlepretre, D. Hemous, R. Martin, and J. Van Reenen. Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy*, 124(1):1–51, 2016.

B. Bartling, R. A. Weber, and L. Yao. Do Markets Erode Social Responsibility? *The Quarterly Journal of Economics*, 130(1):219–266, Feb. 2015. Publisher: Oxford Academic.

R. Bénabou and J. Tirole. Individual and Corporate Social Responsibility. *Economica*, 77(305):1–19, 2010.

R. Bénabou and J. Tirole. Laws and Norms. Working Paper 17579, National Bureau of Economic Research, Nov. 2011. Series: Working Paper Series.

K. Borusyak, P. Hull, and X. Jaravel. Quasi-experimental shift-share research designs. *Review of Economic Studies*, forthcoming.

F. Carlsson, M. Kataria, A. Krupnick, E. Lampi, Åsa Löfgren, P. Qin, T. Sterner, and

X. Yang. The climate decade: Changing attitudes on three continents. *Journal of Environmental Economics and Management*, 107:102426, 2021.

W. M. Cohen, R. R. Nelson, and J. P. Walsh. Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not). Working Paper 7552, National Bureau of Economic Research, Feb. 2000. Series: Working Paper Series.

A. Dechezleprêtre, D. Hémous, M. Olsen, and C. Zanella. Automating Labor: Evidence From Firm-Level Patent Data. SSRN Scholarly Paper ID 3508783, Social Science Research Network, Rochester, NY, Dec. 2019.

J.-L. Duanmu, M. Bu, and R. Pittman. Does market competition dampen environmental performance? Evidence from China. *Strategic Management Journal*, 39(11): 3006–3030, 2018.

J. Eaton, S. Kortum, and F. Kramarz. An Anatomy of International Trade: Evidence From French Firms. *Econometrica*, 79(5):1453–1498, 2011.

A. Falk and N. Szech. Morals and Markets. *Science*, 340(6133):707–711, May 2013. Publisher: American Association for the Advancement of Science Section: Research Article.

D. Fernández-Kranz and J. Santaló. When Necessity Becomes a Virtue: The Effect of Product Market Competition on Corporate Social Responsibility. *Journal of Economics & Management Strategy*, 19(2):453–487, 2010.

R. Fisman, G. Heal, and V. Nair. A model of corporate philanthropy. *Columbia University and University of Pennsylvania*, 2006.

C. Flammer. Does product market competition foster corporate social responsibility? Evidence from trade liberalization. *Strategic Management Journal*, 36(10):1469–1485, 2015.

Gallup. Preference for Environment Over Economy Largest Since 2000. Technical report, 2019. URL `https://news.gallup.com/poll/248243/preference-environment-economy-largest-2000.aspx`.

P. Goldsmith-Pinkham, I. Sorkin, and H. Swift. Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624, August 2020.

O. Hart and L. Zingales. Companies Should Maximize Shareholder Welfare Not Market Value. *Journal of Law, Finance, and Accounting*, 2(2):247–274, 2017.

O. Hawn and H. G. Kang. The market for corporate social responsibility (CSR): How industry structure determines CSR. *Available at SSRN 2380641*, 2013.

Q. Liu, R. Lu, Y. Lu, and T. A. Luong. Import competition and firm innovation: Evidence from china. *Journal of Development Economics*, 151:102650, 2021.

R. G. Newell, A. B. Jaffe, and R. N. Stavins. The Induced Innovation Hypothesis and Energy-Saving Technological Change. *The Quarterly Journal of Economics*, 114(3): 941–975, Aug. 1999. Publisher: Oxford Academic.

W. D. Nordhaus. *Managing the global commons: the economics of climate change*, volume 31. MIT press Cambridge, MA, 1994.

W. D. Nordhaus. Modeling induced innovation in climate-change policy. *Technological change and the environment*, 9:259–290, 2002.

D. Popp. Induced Innovation and Energy Prices. *American Economic Review*, 92(1): 160–180, Mar. 2002.

N. Stern. *The economics of climate change: the Stern review*. cambridge University press, 2007.

X. Vives. Innovation and Competitive Pressure*. *The Journal of Industrial Economics*, 56(3):419–469, 2008.

M. L. Weitzman. A Review of the *Stern Review on the Economics of Climate Change*. *Journal of Economic Literature*, 45(3):703–724, Sept. 2007.

M. L. Weitzman. On Modeling and Interpreting the Economics of Catastrophic Climate Change. *The Review of Economics and Statistics*, 91(1):1–19, Jan. 2009. Publisher: MIT Press.

Table 1: The effects of Values and Competition on the direction of innovation

	(1)	(2)	(3)	(4)
Dependent Variables:	Δ (log (1+clean) - log (1+dirty))	Δ log (1+ clean)	Δ Log (1+dirty)	Δ clean share
		Panel A: The main variables of interest		
ΔValues	0.1461	0.0684	-0.0777	0.0228
	(0.0219)	(0.0209)	(0.0186)	(0.0039)
ΔCompetition	0.0751	0.0185	-0.0566	0.0126
	(0.0379)	(0.0309)	(0.0294)	(0.0073)
ΔValuesXCompetition	0.0286	0.0006	-0.0280	0.0034
	(0.0115)	(0.0100)	(0.0089)	(0.0020)
R^2	0.027	0.034	0.016	0.016
Observations	7,060	7,060	7,060	7,060
		Panel B: Robustness to controlling for fuel price and environmental policies		
ΔValues	0.1149	0.0802	-0.0348	0.0181
	(0.0240)	(0.0230)	(0.0198)	(0.0043)
ΔCompetition	0.0614	0.0228	-0.0386	0.0105
	(0.0376)	(0.0307)	(0.0286)	(0.0073)
ΔValuesXCompetition	0.0240	0.0024	-0.0216	0.0027
	(0.0116)	(0.0101)	(0.0088)	(0.0020)
ΔLog fuel price	0.9607	-0.3084	-1.269	0.1471
	(0.3193)	(0.2913)	(0.2763)	(0.0603)
ΔEPS	0.1141	-0.0620	-0.1761	0.0171
	(0.0999)	(0.0859)	(0.0881)	(0.0194)
R^2	0.029	0.035	0.021	0.017
Observations	7,060	7,060	7,060	7,060
		Panel C: Robustness to adding sectoral and other controls		
ΔValues	0.1633	0.0955	-0.0678	0.0266
	(0.0265)	(0.0262)	(0.0246)	(0.0050)
ΔCompetition	0.0109	0.0028	-0.0082	0.0027
	(0.0402)	(0.0327)	(0.0300)	(0.0079)
ΔValuesXCompetition	0.0415	0.0143	-0.0272	0.0051
	(0.0155)	(0.0138)	(0.0120)	(0.0026)
ΔLog fuel price	0.9505	0.1364	-0.8141	0.1530
	(0.3979)	(0.3707)	(0.3857)	(0.0793)
ΔEPS	0.1712	0.0489	-0.1224	0.0326
	(0.1139)	(0.0944)	(0.0993)	(0.0228)
Fixed-effects				
Sector FE (84)	Yes	Yes	Yes	Yes
HQ country (56)	Yes	Yes	Yes	Yes
Highest country share (25)	Yes	Yes	Yes	Yes
R^2	0.078	0.103	0.053	0.068
Observations	7,060	7,060	7,060	7,060

Note: The difference between the various panels is in terms of controls. Besides the coefficients shown or the fixed effects mentioned, all specifications control for GDP per capita and population. All variables are first differences. Standard errors are robust.

Table 2: Robustness checks

Dependent Variables:	(1) Δ (log (1+clean) - log (1+dirty))	(2) Δ log (1+ clean)	(3) Δ Log (1+dirty)	(4) Δ clean share
		Panel A: Robustness to using other weights		
ΔValues	0.1963	0.1299	-0.0664	0.0355
	(0.0384)	(0.0373)	(0.0324)	(0.0069)
ΔCompetition	0.0391	0.0420	0.0028	0.0054
	(0.0346)	(0.0286)	(0.0256)	(0.0066)
ΔValuesXCompetition	0.0376	0.0083	-0.0293	0.0049
	(0.0153)	(0.0134)	(0.0119)	(0.0026)
ΔLog fuel price	0.6595	-0.3653	-1.025	0.0889
	(0.4194)	(0.3911)	(0.3852)	(0.0804)
ΔEPS	0.0575	0.0349	-0.0226	0.0070
	(0.1420)	(0.1180)	(0.1194)	(0.0273)
Fixed-effects				
Sector FE (84)	Yes	Yes	Yes	Yes
HQ country (56)	Yes	Yes	Yes	Yes
Highest country share (19)	Yes	Yes	Yes	Yes
R^2	0.078	0.103	0.058	0.068
Observations	7,060	7,060	7,060	7,060
		Panel B: Analysis at the firm-country level		
ΔValues	0.00149	0.00420	0.00272	0.000303
	(0.00129)	(0.000938)	(0.00109)	(0.000259)
ΔCompetition	0.000743	0.00203	0.00129	0.000149
	(0.000704)	(0.000480)	(0.000596)	(0.000145)
ΔValuesXCompetition	0.00225	0.00268	0.000432	0.000387
	(0.000667)	(0.000469)	(0.000551)	(0.000133)
ΔLog fuel price	0.141	0.166	0.0250	0.0290
	(0.0111)	(0.00815)	(0.00928)	(0.00222)
ΔEPS	0.0124	0.0104	-0.00193	0.00269
	(0.00143)	(0.00102)	(0.00122)	(0.000299)
Sector FE (84)	Yes	Yes	Yes	Yes
HQ country (56) FE	Yes	Yes	Yes	Yes
Highest country share (25)	Yes	Yes	Yes	Yes
R^2	0.016	0.022	0.012	0.016
Observations	137,925	137,925	137,925	137,925
		Panel C: Computing the standard errors with the methods of Adão et al. (2019)		
ΔValues	0.1633	0.0955	-0.0678	0.0266
	(0.0170)	(0.0067)	(0.0161)	(0.0032)
ΔCompetition	0.0109	0.0028	-0.0082	0.0027
	(0.0054)	(0.0015)	(0.0054)	(0.0010)
ΔValuesXCompetition	0.0415	0.0143	-0.0272	0.0051
	(0.0021)	(0.0006)	(0.0024)	(0.0003)
ΔLog fuel price	0.9505	0.1364	-0.8141	0.1530
	(0.1970)	(0.0780)	(0.1880)	(0.0349)
ΔEPS	0.1712	0.0489	-0.1224	0.0326
	(0.1136)	(0.0274)	(0.1061)	(0.0195)
Fixed-effects				
Sector FE (84)	Yes	Yes	Yes	Yes
HQ country (56)	Yes	Yes	Yes	Yes
Highest country share (25)	Yes	Yes	Yes	Yes
R^2	0.079	0.103	0.054	0.069
Observations	7,060	7,060	7,060	7,060

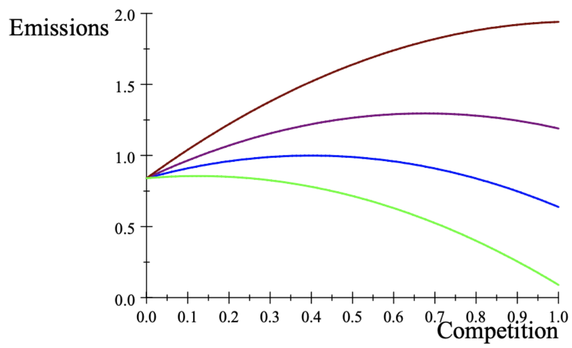
Note: The baseline specification in this table is that of Table 1 panel C. Panel A incorporates GDP in the weight definition. Panel B runs the analysis at the firm-country level. Panel C computes the standard errors with the formula of Adão et al. (2019). Besides the coefficients shown or the fixed effects mentioned, all specifications control for GDP per capita and population. All variables are first differences.

Table 3: Historical and Prospective Counterfactuals

	(1) Actual	(2)	(3)	(4)	(5) Due To	(6)	(7)	(8)	(9)
	$\bigtriangledown$	$\left(\alpha+\gamma\bar{C}\right)$ $\times\Delta V$	$\gamma\left(C-\bar{C}\right)$ $\times\Delta V$	$\left(\beta+\gamma\bar{V}\right)$ $\times\Delta C$	$\gamma\left(V-\bar{V}\right)$ $\times\Delta C$	$\gamma\Delta V$ $\times\Delta C$	$\Delta V,\Delta C$	$\Delta V,\Delta C,$ ΔP	Other
Panel A: Historical									
Clean share change	34.6	-1.9	0.3	0.1	0.1	0.4	-1.1	20.2	14.4
Panel B: Prospective									
Clean share change		4.4	0.8	0.0	0.0	0.1	5.4		
Equiv. $\Delta P/P$ (%)		13.75	2.5	0.0	0.0	0.25	17.0		

Note: Share changes are in percentage points. Column 1 reports historical evolutions; Columns 2 and 3, those due solely to changes in (firms' market exposures to) environmental values ΔV_j and their interactions with (exposures) to competition levels C_j, the average of which is $\bar{C}$; Columns 4 and 5 do the same for changes ΔC_j in competition and their interactions with value levels V_j. Column 6 gives the "second order" effects from interactions between the ΔV_j and ΔC_j. Column 8 computes the total changes attributable to variations in values, competition, and oil prices. Column 9 is the difference between the actual change and the predicted change based on the value, competition and price effects. In unreported results we find that changes in the environmental policy index account for nearly all of "Other". See Appendix B for details.

Figure 1: Effect of competition and social values on pollution

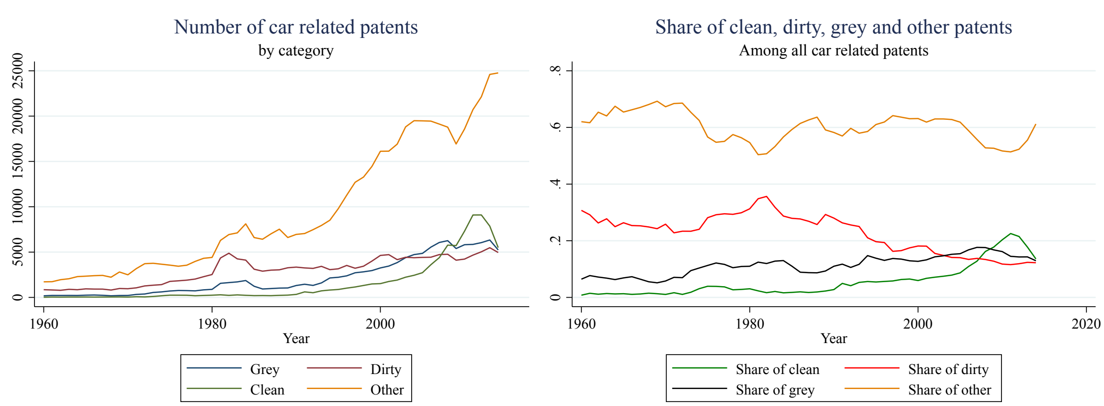


Polluting emissions as a function of market competition, as prosocial attitudes vary from lowest to highest (top to bottom curves)

Figure 2: Evolution over time of clean, dirty, grey and other car related innovations

(a) Absolute number of innovations

(b) Relative share



Source: PATSTAT. Patents classified as clean, dirty, grey or other based on the IPC and Y02 classification systems. See main text and Appendix C.1 for more details.

ONLINE APPENDIX

Appendix A: Proofs

Proof or Proposition 2. For all $\kappa > \kappa_{1,}$, we can write total emissions (9) as:

$$X(\Delta) = \left(1 - \frac{\Delta \pi_M}{\kappa}\right)[1 - 2(1-\Delta)\pi_M] + \frac{\Delta}{\kappa\gamma}\pi_M(1-\pi_M). \tag{A.1}$$

Focusing first on the extremes of full competition and full collusion to get the main intuitions, the former is less polluting than the latter if $X(1) < X(1/2)$, or

$$\begin{aligned} 1 - \frac{\pi_M}{\kappa} + \frac{\pi_M(1-\pi_M)}{\kappa\gamma} &< \left(1 - \frac{\pi_M}{2\kappa}\right)(1-\pi_M) + \frac{\pi_M(1-\pi_M)}{2\kappa\gamma} \iff \\ \frac{\pi_M(1-\pi_M)}{2\kappa\gamma} &< \left(1 - \frac{\pi_M}{2\kappa}\right)(1-\pi_M) - \left(1 - \frac{\pi_M}{\kappa}\right) = \frac{\pi_M(1+\pi_M)}{2\kappa} - \pi_M, \end{aligned}$$

which simplifies to

$$\kappa < 1 - \frac{\gamma^{-\delta}}{2}\left(1 + \frac{1}{\gamma}\right) = \kappa_2, \tag{A.2}$$

where $\kappa_2 > 1 - \gamma^{-\delta} = \pi_M = \kappa_1$ was first defined in Proposition 2. Quite intuitively, for any given κ, (A.2) holds when γ or/and δ is large enough. Let us next determine where X achieves its maximum on $[1/2, 1]$:

$$\kappa \frac{\partial X}{\partial \Delta} = -4\pi_M^2 \Delta + (2\kappa - 1 + 2\pi_M)\,\pi_M + \frac{1}{\gamma}\pi_M(1-\pi_M), \tag{A.3}$$

so $\partial X / \partial \Delta > 0$ if and only if

$$\Delta < \frac{1}{4\pi_M}\left(2\kappa - 1 + 2\pi_M + \frac{1-\pi_M}{\gamma}\right) = \frac{1}{2} + \frac{1}{4\pi_M}\left(2\kappa - 1 + \frac{\gamma^{-\delta}}{\gamma}\right) \equiv \hat{\Delta}_X(\kappa, \gamma, \delta). \tag{A.4}$$

Naturally, $\hat{\Delta}_X$ is increasing in κ and decreasing in both γ and δ. Moreover,

$$\hat{\Delta}_X(\gamma, \delta) < \frac{1}{2} \iff \kappa < \frac{1}{2}\left(1 - \frac{\gamma^{-\delta}}{\gamma}\right) = \kappa_2 - \frac{\pi_M}{2} \equiv \kappa_3, \tag{A.5}$$

$$\hat{\Delta}_X(\gamma, \delta) > 1 \iff \kappa > \kappa_3 + \pi_M = \kappa_2 + \frac{\pi_M}{2} \equiv \kappa_4 \tag{A.6}$$

where $\kappa_2 > \kappa_1 = \pi_M$ was first defined in Proposition 2, by equation (A.2).

It then follows that (maintaining $\kappa > \kappa_1$, thus ensuring an interior optimum for z) :
(i) If $\kappa < \kappa_2 - \kappa_1/2$, Z is decreasing in Δ, and thus minimized at $\Delta = 1$.
(ii) If $\kappa > \kappa_2 + \kappa_1/2$, then Z is increasing in Δ, and thus minimized at $\Delta = 1/2$.
(iii) If $\kappa \in (\kappa_2 - \kappa_1/2, \kappa_2 + \kappa_1/2)$ then X is hump-shaped in Δ, with a maximum at $\hat{\Delta}_X(\gamma, \delta) \in (1/2, 1)$ and a minimum either at 1/2 or at 1, depending on $\kappa \gtreqless \kappa_2$ (recall that this is what defines κ_2).

Note, finally, that conditions $\kappa > \pi_M$ and $\kappa < \kappa_2 - \pi_M/2$ define a nonempty interval when $3\pi_M < 2\kappa_2$, that is, $\gamma^{-\delta}(2 - 1/\gamma) > 1$, or

$$\delta < \ln(2 - 1/\gamma) / \ln \gamma. \blacksquare \tag{A.7}$$

Proof or Proposition 3. From (A.1), when $\kappa > \kappa_1$, we have

$$\kappa \frac{\partial X}{\partial \pi_M} = \frac{\Delta}{\kappa}\left[-1 + 2(1-\Delta)\pi_M + \frac{1-\pi_M}{\gamma}\right] - 2(1-\Delta)\left(1 - \frac{\Delta \pi_M}{\kappa}\right) - \frac{\Delta \pi_M}{\kappa\gamma}. \tag{A.8}$$

The last two terms are clearly negative, and so is the first, since $(1-\pi_M)/\gamma < 1 - \pi_M \leq 1 - 2(1-\Delta)\pi_M$ for all $\Delta \geq 1/2$. Recalling that $\pi_M = 1 - \gamma^{-\delta}$, it follows that $\partial X/\partial \delta < 0$. When $\kappa \leq \kappa_1$, R&D effort may be (depending on Δ) at a corner, $z = 1$, in which case $X = y_M/\gamma = 1/c\gamma^{-\delta-1}$, which decreases in δ. Finally, differentiating (A.3) in π_M,

$$\begin{aligned}
\kappa \frac{\partial^2 X}{\partial \Delta \partial \pi_M} &= -4(1-2\pi_M)\Delta + \frac{1}{\gamma}(1-2\pi_M) - 2\kappa + 2(1-2\pi_M) - 1 \\
&= (1-2\pi_M)\left[\frac{1}{\gamma} + 2 - 4\Delta\right] - 1 - 2\kappa.
\end{aligned}$$

If $1 - 2\pi_M \geq 0$, the right-hand side is bounded above by $(1-2\pi_M)/\gamma - 1 - 2\kappa < 1/\gamma - 1 - 2\kappa < 0$. If $1 - 2\pi_M < 0$, it is bounded above by $(2\pi_M - 1)(2 - 1/\gamma) - 1 - 2\kappa$, since $\Delta \leq 1$; but $\pi_M \leq 1$, so this expression is at most $1 - 1/\gamma - 2\kappa < 0$, since $\kappa > \kappa_1 = \pi_M = 1 - 1/\gamma^\delta > 1 - 1/\gamma$. Therefore, $\partial^2 X/\partial \Delta \partial \delta < 0$ for all Δ, as long as $\kappa > \kappa_1$.

Proof or Proposition 4. *Part (a).* This follows from the conjunction of $\partial X/\partial \Delta < 0$ for $\kappa \prec \kappa_2 - \kappa_1/2$, by Proposition 2, and

$$\frac{\partial U}{\partial \Delta} = \frac{\pi_M}{\kappa}\ln\left(\frac{1}{1 - 2(1-\Delta)\pi_M}\right) + \left(1 - \frac{\Delta \pi_M}{\kappa}\right)\frac{2\pi_M}{1 - 2(1-\Delta)\pi_M} > 0. \tag{A.9}$$

Part (b). Recalling (3), (5) and (10), we can rewrite

$$\text{(A.10)} \qquad U = \left(1 - \frac{\Delta\pi_M}{\kappa}\right) \ln\left(1 - 2(1-\Delta)\pi_M\right) + \ln\left(\frac{1}{c}\right),$$

$$\text{(A.11)} \qquad \frac{\partial U}{\partial \pi_M} = \frac{\Delta}{\kappa} \ln\left(\frac{1}{1 - 2(1-\Delta)\pi_M}\right) - \frac{2(1-\Delta)\pi_M}{1 - 2(1-\Delta)\pi_M}\left(1 - \frac{\Delta\pi_M}{\kappa}\right),$$

Thus, $\partial U/\partial \pi_M > 0$ if and only if

$$\text{(A.12)} \qquad \kappa < \Delta\left[\pi_M + f\left(\frac{2(1-\Delta)\pi_M}{1 - 2(1-\Delta)\pi_M}\right)\right],$$

where $f(t) \equiv \ln(1+t)/t$ for all $t > 0$ and $f(0) \equiv \lim_{t\to 0} f(t) = 1$. Note that f is a decreasing function, since $f'(t)$ has the sign of $g(t) \equiv t - (1+t)\ln(1+t)$, where clearly $g'(t) < 0 = g(0)$ for all $t > 0$. The right-hand side of (A.12) is thus increasing in Δ, so the inequality holds if and only if $\Delta > \underline{\Delta}(\pi_M, \kappa)$, with

$$\text{(A.13)} \qquad \underline{\Delta}(\pi_M, \kappa) < 1 \iff \kappa < 1 + \pi_M,$$

$$\text{(A.14)} \qquad \underline{\Delta}(\pi_M, \kappa) < 1/2 \iff \kappa < \frac{1}{2}\left[\pi_M + f\left(\frac{\pi_M}{1-\pi_M}\right)\right] \equiv \bar{\kappa}(\pi_M),$$

Condition (A.13) is always compatible with $\kappa > \pi_M$ and $\kappa < \kappa_2 - \pi_M/2$. Condition (A.14), which ensures that $\partial U/\partial \pi_M > 0$ for all values of $\Delta \in [1/2, 1]$, is more demanding since $\bar{\kappa}(\pi_M) < (1+\pi_M)/2$ and compatible with $\kappa > \pi_M$, only if

$$\text{(A.15)} \qquad \pi_M < f\left(\frac{\pi_M}{1-\pi_M}\right) = \frac{\ln\left[1/(1-\pi_M)\right]}{\pi_M/(1-\pi_M)} \iff \pi_M^2 < (1-\pi_M)\ln\left(\frac{1}{1-\pi_M}\right),$$

which holds for instance when π_M is small enough, meaning that $\delta \ln \gamma$ is small enough. This finishes to establish (b).

Part (c). In (A.9), the first term is increasing in π_M, and while the second not always is, a sufficient condition is that $(\Delta\pi_M/\kappa)(1 - \Delta\pi_M/\kappa)$ be increasing, which occurs for $\Delta\pi_M/\kappa < 1/2$; conversely, $\pi_M/\kappa < 1/2$ is necessary the second term for that same term to be increasing in Δ up to $\Delta = 1$. Thus, when $\kappa > 2\pi_M = 2\kappa_1$, we have $\partial^2 U/\partial\Delta\partial\delta > 0$, hence the result since $\partial^2 X/\partial\Delta\partial\delta > 0$.

We check, finally, that this new lower bound on κ is compatible with key upper bounds previously defined, meaning that they jointly define a nonempty set of values for (κ, γ, δ). We have:

$$
\begin{aligned}
2\pi_M &< \kappa_2 - \pi_M/2 \iff 5(1-\gamma^{-\delta}) < 2\kappa_2 = 2 - \gamma^{-\delta}(1+1/\gamma) \iff \\
\text{(A.16)} \quad \delta &< \frac{\ln(4/3 - 1/3\gamma).}{\ln \gamma}. \\
2\pi_M &< \bar{\kappa}(\pi_M) \iff 3\pi_M < f\left(\frac{\pi_M}{1-\pi_M}\right) = \frac{\ln\left[1/(1-\pi_M)\right]}{\pi_M/(1-\pi_M)} \\
\text{(A.17)} \quad &\iff 3\pi_M^2 < (1-\pi_M)\ln\left(\frac{1}{1-\pi_M}\right).
\end{aligned}
$$

The first condition is naturally tighter than (A.7), so when it holds we have $\partial^2 U/\partial\Delta\partial\delta > 0$ for all Δ and $\partial U/\partial\delta > 0$ for Δ in some nonempty interval $(\underline{\Delta}, 1]$. If the second condition also holds (which is ensured by some additional upper bound on δ), then $\partial^2 U/\partial\Delta\partial\delta > 0 > \partial U/\partial\delta > 0$ for all $\Delta \in [1/2, 1]$. This, together with the fact that, from Proposition 2, $\partial^2 X/\partial\Delta\partial\delta \prec 0$ for all $\kappa \succ \kappa_1$, establishes Part (c). ∎

Appendix B: Counterfactual Methodology

We can write our regression model in equation (12) as

$$
\text{(B.1)} \qquad Z_{j,t} \equiv \ln\left(PAT_{j,t} + 1\right) = \alpha V_{j,t} + \beta C_{j,t} + \gamma V_{j,t} \times C_{j,t} + \varphi F_{j,t} + \varepsilon_{j,t},
$$

where, for each firm j and time t, $PAT_{j,t}$ is the number of patents (families) of a given type (clean or dirty), $V_{j,t}$ and $C_{j,t}$ are its (average) degrees of exposure to prosocial values and competition respectively, and $F_{j,t}$ collects all other explanatory variables, such as oil prices, firm and period fixed effects, etc.

Denoting $\Delta X_{j,t} = X_{j,t} - X_{j,\tau}$ any historical or counterfactual change between dates τ and t, and given estimated coefficients $(\hat{\alpha}, \hat{\beta}, \hat{\gamma}, \hat{\varphi})$, the implied patenting level at t is

$$
\text{(B.2)} \qquad \widehat{PAT}_{j,t} = (PAT_{j,\tau} + 1) \times \exp(\widehat{\Delta Z}_j) - 1,
$$

where (omitting time subscripts to lighten the notation):

$$
\text{(B.3)} \quad \widehat{\Delta Z}_j \equiv \hat{\alpha}\Delta V_j + \hat{\beta}\Delta C_j + \hat{\gamma}(\Delta V_j \times C_j) + \hat{\gamma}(V_j \times \Delta C_j) + \hat{\gamma}(\Delta V_j \times \Delta C_j) + \hat{\varphi}\Delta F_j.
$$

For small changes, $\widehat{\Delta PAT}_j$ is proportional to $\widehat{\Delta Z}_j$, and can thus be decomposed into the constituents of (B.3). Alternatively, one can use the fitted nonlinear model for counterfactual analysis, asking: "How much would the total patents of each type have increased or decreased between τ and t, if the *only* changing factor had been the variations in environmental values observed in the different countries, and thus firms' exposures $V_{j,t}$?" Or, replacing historical accounting by prospective simulations: "How much should we expect those patent numbers to increase between τ and (some future) t, if the only changing factor will be some assumed set of ΔV's (or/and ΔC's?"

The answer is obtained by setting, for each j, all terms in (B.3) to zero except for $\hat{\alpha}\Delta V_j + \hat{\gamma}(\Delta V_j \times C_j)$, then summing across firms the resulting $\widehat{\Delta PAT}_j$'s computed from (B.2). This total change can itself be attributed to the combination of a direct, "average" effect of the ΔV_j's (weighted by initial patenting activity), and one that reflects their *interaction,* and therefore their *correlation* pattern, with initial levels of competition, C_j. This is again clearest when understood as a first-order approximation,

$$
\begin{aligned}
\widehat{\Delta PAT} &\equiv \sum_j \widehat{\Delta PAT}_j \approx \sum_j (PAT_j + 1)\,\widehat{\Delta Z}_j \\
&= \hat{\alpha} \sum_j (PAT_j + 1)\,\Delta V_j + \hat{\gamma} \sum_j (PAT_j + 1)\, C_j \times \Delta V_j \\
&= \left(\hat{\alpha} + \hat{\gamma}\bar{C}\right) \sum_j (PAT_j + 1)\,\Delta V_j + \hat{\gamma} \sum_j (PAT_j + 1)\left(C_j - \bar{C}\right) \Delta V_j, \qquad \text{(B.4)}
\end{aligned}
$$

where $\bar{C} \equiv (1/N) \sum_j (PAT_j + 1)\, C_j$ is the average level of (firm exposure to) competition, with each firm weighted by its initial patenting activity. Alternatively, to get exact numbers we can simulate the nonlinear model, by:

(a) Setting, for all j, all changes in (B.3) except ΔV_j to zero, and equating all C_j's to $\bar{C}$; the results for clean, grey and dirty patents are given in Column 2 of Table 3. They correspond to what would have happened if every firm had faced the (patent-weighted) average attitudinal *change*, and the (patent-weighted) average *level* of market competition.

(b) Setting all terms but the $\hat{\gamma}(\Delta V_j C_j)$'s to zero, and subtracting $\hat{\gamma}\bar{C} \sum_j (PAT_j + 1) \times \Delta V_j$. This yields the results in Column 3, reflecting the (patent-weighted) extent to which firms that saw larger ΔV_j's in their markets were exposed there to higher or lower levels of competition.

Similarly, Columns 4 and 5 in Panel A compute the counterfactual changes in each number of patents (relative to total) corresponding to historical changes in competition *only,* doing so separately for the effect of the (patent-weighted) average change, evaluated at the mean level of environmental values, $\left(\hat{\beta} + \hat{\gamma}\bar{V}\right) \sum_j (PAT_j + 1) \times \Delta C_j$, and that reflecting the correlation pattern with initial attitudes, $\hat{\gamma} \sum_j (PAT_j + 1) \left(V_j - \bar{V}\right) \times \Delta C_j$, where $\bar{V} \equiv (1/N) \sum_j (PAT_j + 1) V_j$.

Column 7 incorporates all the above effects, plus those of the interaction in *changes,* $\hat{\gamma}(\Delta V_{jt} \times \Delta C_{j,t})$. Column 8 adds to the effects of column 7 those due to variations in oil prices.

The prospective exercise reported in Panel B of Table 3 is identical, except that the initial date is $\tau = 2012$ and the counterfactual $\Delta V_{j,t}$'s and $\Delta C_{j,t}$'s are taken to be *uniform* across firms, equal respectively to 0.78 and 0.08 standard deviations. As explained in Section 6 (see also Table B.1), these magnitudes are the historical ones observed in our sample, but with a sign reversal for the former –in line with the fact that, since 2012 (when our patent dataset ends), the previous general decline environmental values seems to have given way to an upswing.

Table B.1: Descriptive Statistics for Counterfactual Calculations

	Unweighted					Patent-Weighted	
	Mean	Std.Dev.	P1	P50	P99	Mean	Std.Dev.
$\Delta Values$	-0.779	0.761	-1.614	-1.059	2.454	0.142	1.630
$\Delta Comp$	0.085	0.405	-0.754	0.000	1.713	0.311	0.600
$(Comp - \overline{Comp}) \times \Delta Values$	-0.159	1.122	-2.001	-0.159	3.201	0.305	1.747
$\left(Values - \overline{Values}\right) \times \Delta Comp$	0.004	0.017	-0.033	0.000	0.074	0.013	0.026
$\Delta log(FuelPrice)$	1.752	0.145	1.645	1.693	2.377	1.814	0.180

Note: Patent weighting is defined in equation B.4, using firms' clean patent levels in 2002.

Table B.2: Correlations between key variables

	Clean	Dirty	Values	Competition	ΔValues	ΔCompetition
Clean	1.000					
Dirty	0.596	1.000				
Values	-0.050	-0.048	1.000			
Competition	0.080	0.051	-0.114	1.000		
ΔValues	0.104	0.123	-0.589	0.090	1.000	
ΔCompetition	0.039	0.047	0.000	0.004	0.256	1

Note: Clean, Grey and Dirty correspond here to (one plus) each firms' number of patents in each category, in the 1997-2002 time period. The measures of Values and Competition also refer to the 1997-2002 sample period. The differenced variables refer to the difference between the 2008-2012 and the 1997-2002 time period.

Appendix C: Details on variable definition

C1. Classifying patents as clean, dirty or grey

Table C.1 reports the Cooperative Patent Classification (CPC) classification used to determine the different flavours of innovation.[17]

Table C.1: Patent CPC classification codes used

Clean	
Y02T10/60	Other road transportation technologies with climate change mitigation effect
Y02T10/70	Energy storage for electromobility
Y02T90/10	Technologies related to electric vehicle charging
Y02T90/34	Fuel cell powered electric vehicles
Y02T90/42	Hydrogen as fuel for road transportation
Grey	
Y02T10/10	Climate change mitigation technologies related to fuel injection
Y02T10/20	Climate change mitigation technologies related to exhaust after treatment
Y02T10/40	Climate change mitigation technologies related to engine Management Systems
Y02T10/50	Climate change mitigation technologies related to Intelligent Control Systems
Dirty	
F02	Combustion Engines
Other Automotive	
B60	Vehicles in General

C2. Values

The data on attitudes comes from the International Social Survey Program (ISSP) and the World Value Survey (WVS). Several questions could capture the values we are interested in, but they are often asked only in a limited set of countries during a single survey wave. Only one question is common to both surveys, allowing us to cover many countries for two time periods. In the ISSP, it is: *How willing would you be to pay much higher taxes in order to protect the environment?;*and in the WVS, *Can you tell me whether you strongly agree, agree, disagree or strongly disagree with the following statement: 'I would agree to an increase in taxes if the extra money were used to prevent environmental pollution'.* In both cases, answers are given on a 5-point scale. Answers to the ISSP question vary from 1 ('very willing') to 5 ('very unwilling')

[17]See `https://www.cooperativepatentclassification.org/index`, as well as also `https://www.wipo.int/classifications/ipc/en/` and `https://www.epo.org/news-issues/issues/classification/classification.html`.

and we reverse-code them, so that a higher value means a more pro-environmental attitude. In the WVS, answers to the corresponding question are 1 ('strongly agree'), 2 ('agree'), 4 ('disagree') and 5 ('strongly disagree'). We code as 3 the 'don't know' answers and reverse-code the others, as for the ISSP.

Because taxes pertain to public policy more directly than to consumer spending decisions, we also use one additional variable from each survey to create a synthetic index. For ISSP, the question is: *How willing would you be to pay much higher prices in order to protect the environment?* For the WVS, it is about (dis)agreement with the statement: *I would give part of my income if I were certain that the money would be used to prevent environmental pollution* . To ensure consistency, we code all answers so that higher values mean more pro-environmental attitudes. We then average all variables at the country-period level, transform them into z-scores, and average across all variables available for the country-period observation. We thus have data on willingness-to-pay for the environment for 25 countries for 2 periods, namely 2000 and 2010. Our data cover most major economies, and in particular most countries in which firms innovating in the automotive sector reside, with a few notable exceptions such as Italy and Spain.

C3. Computation of firm-level Lerner Index

We estimate firm-level measures of competition using a (revenue) production function framework. We assume a homothetic translog production function with materials $M_{i,t}$ and labor $L_{i,t}$ as flexible factors, and capital $K_{i,t}$ a quasi-fixed production factor. A firm's (log) revenue ($R_{i,t}$) growth can then be written as

$$\Delta r_{i,t} \approx \frac{\lambda}{\bar{\mu}_{i,t}} + \bar{s}_{Mi,t}\left(\Delta m_{i,t} - \Delta k_{i,t}\right) + \bar{s}_{Li,t}\left(\Delta l_{i,t} - \Delta k_{i,t}\right) + \frac{1}{\bar{\mu}_{i,t}} \Delta\omega_{i,t}, \tag{C.1}$$

where $\Delta r_{i,t} = \ln(R_{i,t}/\ln R_{i,t-1})$ (and equivalently for production factors), λ is a scale parameter, $\bar{s}_{Mi,t} = \left(s_{Mi,t} + s_{Mi,t-1}\right)/2$ the average share of materials expenditure in revenue between period t and $t-1$ (and equivalently for labor inputs), and $\omega_{i,t}$ a Hicks- neutral shifter of TFP or/and demand. $\bar{\mu}_{i,t}$ is the average markup of prices over marginal cost between period t and $t-1$, making $\bar{\mu}_{i,t}$ -1 a Lerner index specific to firm i at time t. Short run profit maximization implies

$$s_{Mi,t} = \frac{\alpha_{Mi,t}}{\mu_{i,t}}, \tag{C.2}$$

where $\alpha_{Mi,t}$ is the elasticity of output with respect to changes in production factor M (and analogously for labor). Note that in the translog case,

$$\alpha_{Mi,t} = \alpha_M + \alpha_{KM} k_{i,t} + \alpha_{LM} l_{i,t} + \alpha_{MM} m_{i,t}. \tag{C.3}$$

This specification is consistent with a wide variety of market structures. For further discussion see Martin (2012) and Forlani (2016). We can rewrite (C.1) as

$$\Xi_{i,t} \frac{\bar{\alpha}_{Mi,t}}{\lambda} - \Delta k_{i,t} = \frac{1}{\lambda} \Delta \omega_{i,t}, \tag{C.4}$$

where

$$\Xi_{i,t} \equiv \frac{\Delta r_{i,t} - \frac{\lambda}{\bar{\mu}_{i,t}} + \bar{s}_{Mi,t} \left(\Delta m_{i,t} - \Delta k_{i,t}\right) + \bar{s}_{Li,t} \left(\Delta l_{i,t} - \Delta k_{i,t}\right)}{\bar{s}_{Mi,t}}.$$

Given assumptions on the evolution of the $\Delta \omega_{it}$ shock, we can fit this to firm-level data using a GMM approach. Thus, if $\Delta \omega_{i,t}$ follows an AR(1) process, $\omega_{i,t} = \rho \omega_{i,t-1} + \eta_{i,t}$ where $\eta_{i,t}$ is iid, we can write

$$\hat{\eta}_{i,t} = \Xi_{i,t} \frac{\bar{\alpha}_{Mi,t}}{\lambda} - \Delta k_{i,t} - \frac{\rho}{\lambda} \left[\Xi_{i,t-1} \frac{\bar{\alpha}_{Mi,t-1}}{\lambda} - \Delta k_{i,t-1} \right],$$

and estimate the parameters $\delta = [\rho/\lambda, \alpha_M/\lambda, \alpha_{KM}/\lambda, \alpha_{LM}/\lambda, \alpha_{MM}/\lambda]$ using the moment conditions:

$$E \left[\hat{\eta}_{i,t} \times \left\{ \Xi_{i,t-1}, \frac{1}{\Delta k_{i,t}}, \frac{\bar{k}_{i,t}}{\Delta k_{i,t}}, \frac{\bar{l}_{i,t}}{\Delta k_{i,t}}, \frac{\bar{m}_{i,t}}{\Delta k_{i,t}} \right\} \right] = 0.$$

After identifying δ, we can compute $\widehat{\alpha_{Mi,t}/\lambda}$ using (C.3). Then, from (C.2) we can compute

$$\widehat{\frac{\lambda}{\mu_{i,t}}} = s_{Mi,t} \left(\widehat{\frac{\alpha_{Mi,t}}{\lambda}} \right)^{-1}, \tag{C.5}$$

which is an inverse Lerner Index, scaled by the returns to scale parameter λ; i.e. it tells us the excess of markups over returns to scale. While this is different from the markup over marginal costs, it is more relevant in terms of measuring market power, as revealed by excess earnings over what would be reasonable to compensate for increasing returns. We also implement a simpler version, assuming a Cobb Douglas production function, so that $\alpha_{Mi,t} = \alpha_M$. Both approaches lead to similar results.

Note that these firm-level measures, focusing specifically on the automobile sector, display much less heterogeneity in trends than the country-level indicators. Panel (a) of Figure A2 shows deciles of the distribution of markups over marginal costs – i.e., the inverse of the Lerner Index – across firms. It indicates that markups (and thus competition) have been flatlining over time, with the exception of the top decile, where we see an upward trend from 2003 onwards. Panel (b) shows changes in market power for continuing firms between 2002 and 2012: for the majority of automobile firms, the general picture is that of a *reduction in market power* during that time period.

C4. Exogenous competition indicators

We provide here more details on our construction of country and sector-specific competition indicators. Consider a simplified version of our main regression equation (12):

$$\Delta Innovation_j = \beta \Delta Competition_j + \varepsilon_j,$$

where competition is computed as the change in the inverse Lerner Index measured via markups $\mu_{j,t}$. Let us focus, for simplicity, on obtaining an unbiased estimate of the causal effect of competition β. A central concern is that shocks to innovation lead, almost by definition, to increases in market power, which could translate into lower competition measured as markups. Furthermore, an innovation shock to firm j could also affect other firms that operate in the same sector. Our identification assumption is that such effects only operate within 4-digit sectors.

Suppose that all firms in our sample produced for one country $c(j)$ only. Our strategy would then boil down to creating an indicator of exogenous shocks to competition, $\hat{comp}_{c(j),s(j),t}$ for each firm j, by averaging over the inverse markups for firms i in the same 2-digit sector as firm j but excluding those in the same 4-digit sector as firm j:

$$\hat{comp}_{c(j),s(j),t} = Mean\left(\frac{1}{\mu_{i,t}}|s(i) = s(j) \text{ and } s4dig(i) \neq s4dig(j)\right). \tag{C.6}$$

Consequently, we can use as an index for changes in competition exposure for firm j

$$\Delta\hat{comp}_j = \hat{comp}_{c(j),s(j),t} - \hat{comp}_{c(j),s(j),t-1}, \tag{C.7}$$

so that $\Delta\hat{comp}_j \perp \varepsilon_j$.

In practice, the firms in our sample operate across several countries, which we measure by the share of patenting across various jurisdictions c via the weights $w_{c,j}$. To obtain exogenous shocks to competition for each firm j, we run regressions

$$\frac{1}{\mu_{i,t}} = \sum_c comp_{c,s(i),t} w_{c,i} + \varepsilon_{i,t} \tag{C.8}$$

over the sample of firms i such that $s(i) = s(j)$ and $s4dig(i) \neq s4dig(j)$. We then obtain a firm-level competition index for firm j as

$$\Delta \hat{comp}_j = \sum_c \left(\hat{comp}_{c,s(j),t} - \hat{comp}_{c,s(j),t-1} \right) w_{c,j} \tag{C.9}$$

In the special case where a firm only operates in one country (C.8) and (C.9) are equivalent to (C.6) and (C.7).

Appendix D: Details on the Bartik research design

Suppose (clean) innovation by firm j at time t can be described as

$$I_{j,t} = J_j + \alpha S_{j,t} + \varepsilon_{j,t}$$

where, for simplicity, we consider only one Bartik-style variable

$$S_{j,t} = \sum_c w_{j,c} S_{c,t},$$

in which the $S_{c,t}$ are country-level shocks (e.g., pro-social attitudes) and the $w_{j,c}$ are firm-level weights measuring a firm's exposure to a particular country. J_j is a firm fixed effect. We assume that country-level shocks $S_{c,t}$ and firm-level shocks $\varepsilon_{j,t}$ can be decomposed as follows:

$$S_{c,t} = J_c + c_{c,t} + \eta_{c,t}, \tag{C.10}$$

$$\varepsilon_{j,t} = \gamma N_{j,t} + c_{c(j),t} + \nu_{j,t},$$

where

$$N_{j,t} = \sum_c w_{j,c} N_{c,t}$$

and the $N_{c,t}$ are additional country-level shocks that are affecting firm-level outcomes in accordance with firm-level exposure. We assume that the $N_{c,t}$ are not correlated with the $S_{c,t}$, i.e. $S_{c,t} \perp N_{c,t}$. $c_{c(j),t}$ is a time-varying country-level factor (where $c(j)$ denotes the country where firm j is based/headquartered). It is meant to capture specific capabilities that might emerge in a particular country (e.g., a strong supply-chain ecosystem favourable to clean technologies), which we also allow to feed into country level variables such as social attitudes (see equation C.10). J_c is a fixed component in the country-level shock, while $\nu_{j,t}$ and $\eta_{c,t}$ are iid.

In our baseline, we allow that weights could be determined by fixed country- and firm-level characteristics,

$$w_{j,c} = f(J_j, J_c) + \xi_{j,c}.$$

For instance, when firms established their patenting strategy during the pre-sample period, this may have been based on long-standing country characteristic known at the time, as well as on persistent firm capabilities. However, because ε_{jt} and ν_{jt} are iid, we can purge potential endogeneity by first differencing our regression equations:

$$\Delta I_j = \alpha \Delta S_{j,t} + \Delta \varepsilon_{j,t}, \tag{C.11}$$

with

$$\Delta \varepsilon_{j,t} \perp w_{j,c}. \tag{C.12}$$

Note that (C.12) also ensures that

$$\sum_c w_{j,c} c_{c,t} \perp \Delta \varepsilon_{j,t}. \tag{C.13}$$

Next, since,

$$\Delta S_{j,t} = \sum_c w_{j,c} \left(\Delta c_{c,t} + \Delta \eta_{c,t} \right),$$

we also have $\Delta S_{j,t} \perp \Delta \varepsilon_{j,t}$, and thus (C.11) will provide an unbiased estimate of α. Similarly, $N_{j,t}$ will be independent between observations, so that no non-standard clustering is needed to estimate standard errors.

Alternatively, we can assume that persistent firm-level characteristic also influence innovation trends; our equation for firm level shocks would then be of the form

$$\varepsilon_{j,t} = \kappa J_{j,t} + \gamma N_{j,t} + c_{c(j),t} + \nu_{j,t},$$

where $\kappa J_{j,t}$ is a firm-specific trend. Note that the differenced Bartik explanatory variable $S_{j,t}$ remains orthogonal to most of the differenced firm level shocks

$$\Delta\varepsilon_{j,t} = \kappa J_j + \Delta N_{j,t} + \Delta c_{c(j,)t} + \Delta\nu_{j,t},$$

$$\Delta S_{j,t} \perp \kappa J_j, \Delta N_{jt}, \Delta\nu_{jt}.$$

However, because the weights $w_{j,c}$ are now correlated with the κJ_j part of the $\Delta\varepsilon_{j,t}$, we can no longer assume $\Delta S_{j,t} \perp \Delta\varepsilon_{j,t}$. This is easiliy rectified by including headquarter dummies $\alpha_{c(j)}$ in the regression equation, which becomes

$$\Delta I_j = \alpha\Delta S_{j,t} + \alpha_{c(j)} + \Delta\chi_{j,t},$$

where $\chi_{j,t} = \gamma\Delta N_{j,t} + \kappa J_j + \nu_{j,t}$. Because weights are no longer random, we can no longer assume $\Delta N_{j,t} \perp \Delta N_{i,t}$. To deal with this issue, we use the standard-error adjustment proposed by Adão et al. (2019). Finally, note that in addition to the $N_{c,t}$, we might have country-level shocks $O_{c,t}$ that are correlated with the $S_{c,t}$ and also affect firm innovation (e.g. fuel prices, R&D subsidies etc.). In that case, firm-level shocks would have the following structure:

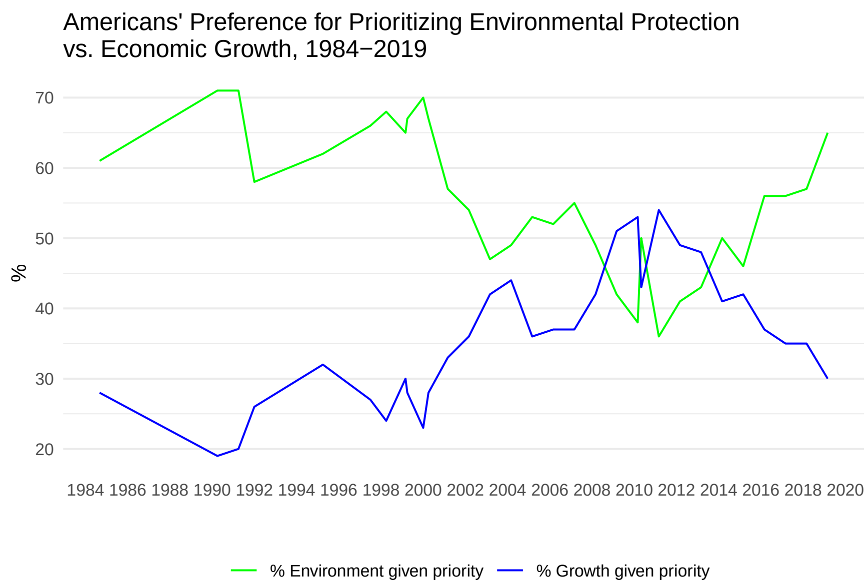
$$\varepsilon_{j,t} = \kappa J_{j,t} + \gamma N_{j,t} + \beta O_{j,t} + c_{c(j),t} + \nu_{j,t},$$

where $O_{j,t} = \sum_c w_{j,c} O_{c,t}$. To still obtain an unbiased estimate for α, we then need to include $O_{j,t}$ in the regression equation

$$\Delta I_j = \alpha\Delta S_{j,t} + \beta O_{j,t} + \alpha_{c(j)} + \Delta\chi_{j,t}.$$

Appendix Figures

Figure A1: Long run decline and recent reversal in pro-environmental concerns

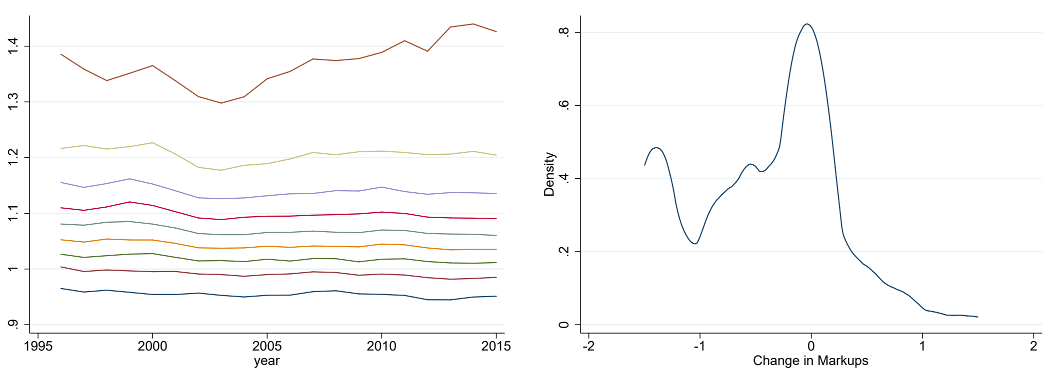


Notes: Based on responses to the question "With which one of these statements about the environment and the economy do you most agree - protection of the environment should be given priority, even at the risk of curbing economic growth (or) economic growth should be given priority, even if the environment suffers to some extent" Source: Gallup (2019)

Figure A2: Firm-level Markups

(a) Distribution over time

(b) Change between the 2 periods



Notes: Panel (a) shows centiles (10th to 90th percentile) of firm-level markups (inverse of the Lerner index) over time. Panel (b) shows the distribution of changes in markups between 2002 and 2012. These markups are computed using ORBIS data.

CENTRE FOR ECONOMIC PERFORMANCE
Recent Discussion Papers

1683	Georg Graetz	Labor Demand in the Past, Present and Future
1682	Rita Cappariello Sebastian Franco-Bedoya Vanessa Gunnella Gianmarco Ottaviano	Rising Protectionism and Global Value Chains: Quantifying the General Equilibrium Effects
1681	Felipe Carozzi Christian Hilber Xiaolun Yu	On the Economic Impacts of Mortgage Credit Expansion Policies: Evidence from Help to Buy
1680	Paul Frijters Christian Krekel Aydogan Ulker	Machiavelli Versus Concave Utility Functions: Should Bads Be Spread Out Or Concentrated?
1679	Antoine Dechezleprêtre David Hémous Morten Olsen Carlo Zanella	Automating Labor: Evidence from Firm-Level Patent Data
1678	Michael Amiior	The Contribution of Immigration to Local Labor Market Adjustment
1677	Swati Dhingra Silvana Tenreyro	The Rise of Agribusiness and the Distributional Consequences of Policies on Intermediated Trade
1676	Jeffrey Grogger Ria Ivandic Tom Kirchmaier	Comparing Conventional and Machine-Learning Approaches to Risk Assessment in Domestic Abuse Cases
1675	Mary Amiti Stephen J. Redding David E. Weinstein	Who’s Paying for the U.S. Tariffs? A Longer-Term Perspective
1674	Cheng Chen Claudia Steinwender	Import Competition, Heterogeneous Preferences of Managers and Productivity

1673	Stefano Bolatto Alireza Naghavi Gianmarco Ottaviano Katja Zajc Kejzar	Intellectual Property and the Organization of the Global Value Chain
1672	Timothy Besley Isabel Roland John Van Reenen	The Aggregate Consequences of Default Risk: Evidence from Firm-Level Data
1671	Jan-Emmanuel De Neve Daisy Fancourt Christian Krekel Richard Layard	A Local Community Course That Raises Mental Wellbeing and Pro-Sociality
1670	Tommaso Sonno	Globalization and Conflicts: The Good, the Bad and the Ugly of Corporations in Africa
1669	Michael Amior	Immigration, Local Crowd-Out and Undercoverage Bias
1668	Antoine Berthou John Jong-Hyun Chung Kalina Manova Charlotte Sandoz Dit Bragard	Trade, Productivity and (Mis)allocation
1667	Holger Breinlich Elsa Leromain Dennis Novy Thomas Sampson	Exchange Rates and Consumer Prices: Evidence from Brexit
1666	Fabrice Defever Michele Imbruno Richard Kneller	Trade Liberalization, Input Intermediaries and Firm Productivity: Evidence from China
1665	Philippe Aghion Antonin Bergeaud Richard Blundell Rachel Griffith	The Innovation Premium to Soft Skills in Low-Skilled Occupations

The Centre for Economic Performance Publications Unit
Tel: +44 (0)20 7955 7673 Email info@cep.lse.ac.uk
Website: http://cep.lse.ac.uk Twitter: @CEP_LSE