Environmental Preferences and Technological Choices : Is Market Competition Clean or Dirty?*

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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 8,562 automobile-sector firms in 41 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.

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1 Introduction

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 the direct, short-run impact of competition on the environment is always negative –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.

In the second part of the paper, we 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 firm-specific measures of exposure to pro-environmental attitudes and competition. Our data covers 8,562 firms and 41 countries during 1998-2002 and 2008-2012, with around 100,000

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

[2]The examples of China or India today, or of the increasing market share of SUV everywhere since the 1980s, are quite illustrative in that respect. Another example is increasing worldwide competition in the airline industry, resulting in increasing travel and emissions.

patents filed in the first period and 150,000 in the second. A firm's exposure is defined as a weighted average of country-level measures of the corresponding variable, where the weights proxy for the importance of the various countries to the firm. For competition, we also construct a firm-level, Lerner-type index. We find a significant positive effect of pro-environment attitudes on the probability for a firm to patent relatively more in the clean direction, and this effect is stronger, the higher competition is. In particular, 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 34% 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, a number of 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 and Stern (2007) and Weitzman (2007, 2009)

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

2 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.

2.1 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 F_j) , he achieves consumption utility

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

where

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

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. The parameter 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 F_j with the highest price/quality ratio, q/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.

2.2 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.

Suppose that 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, be 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.

2.3 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.

$$
\begin{aligned}
p(\Delta) &= \frac{c}{1-2\,(1-\Delta)\,\pi_M} = \frac{c}{1-2\,(1-\Delta)\,(1-\gamma^{-\delta})} \in [c, p_M], & (4)\\
y(\Delta) &= \frac{1}{p(\Delta)} = \frac{1}{c}\left[1-2\,(1-\Delta)\,(1-\gamma^{-\delta})\right] \in \left[y_M, \frac{1}{c}\right]. & (5)
\end{aligned}
$$

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.

2.4 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 parameter values such that

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

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

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

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 $I \equiv z(\Delta)$.

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.

2.5 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 $\kappa_2 \equiv 1 - \gamma^{-\delta}(1 + 1/\gamma)/2 > \kappa_1$ and let $\kappa > \kappa_1$, so that the optimal $z(\Delta)$ is always interior. 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 $\Delta = 1$.

This proposition and the next are illustrated in Figure 1, and proved in the Appendix.

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

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[6]

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

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. We show in the Appendix:

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) For $\kappa \geq 2\kappa_1$, preferences and competition are complements, $\partial^2 W/\partial\Delta\partial\delta > 0$.*

3 Empirical Strategy

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

$$\begin{aligned} Innovation_{j,t} = {} & \alpha Values_{j,t} + \beta Competition_{j,t} + \gamma Values_{j,t} \times Competition_{j,t} \\ & + \delta X_{j,t} + J_j + T_t + \varepsilon_{j,t} \end{aligned} \tag{12}$$

[6]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.

In our preferred specification, $Innovation_{j,t}$ is the number of clean patents that firm j filed in period t, *relative to dirty ones*, measured as *log(1+number of clean patents)* − *log(1+number of dirty patents).* We also examine clean and dirty patents separately. The J_j are firm fixed effects, and the T_t period fixed effects for t = 1998-2002 or 2008-2012. We restrict the analysis to these two periods because of data constraints (see below).

$Values_{j,t}$ is a firm-specific measure of exposure to pro-environmental values, defined as a weighted average of country-level measures, $values_{c,t}$:

$$Values_{j,t} = \sum_{c=1}^{41} \omega_{j,c} \times values_{c,t},$$

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 41 countries for which we have data on both environmental values and competition.

Our main competition measure for firm j in period t is similarly defined as a weighted average of country-level indicators. For a subset of firms, we also use a firm-level measure that can be interpreted as a Lerner index (see Appendix C). Finally, the $X_{j,t}$ are controls, including GDP per capita, population, (tax-inclusive) oil prices and, in some specifications, environmental policies. They are again defined for each firm as a weighted average of country-level variables, with weights computed as above.

4 Data

4.1 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 an innovation-intensive one where patents are perceived as an effective means of protection against imitation, something not true in all sectors (Cohen et al., 2000). Any given 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 patent 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 label as "grey" technologies those that improve the efficiency of the ICE, and as "other" all car-related innovations that do not fit into these three categories (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 very rapidly. Our sample consists of all firms in the industry that patented at least once during either 1998-2002 or 2008-2012.[7] This yields 8,562 firms, out of which 2,130 patented in both periods. In 1998-2002, conditional on patenting, the average number of innovations per firm is 2.3 clean ones and 6.1 dirty ones; in 2008-2012, these figures are respectively 6 and 3.7. On average, firm-level growth rates between the two periods are 34% for clean patents 4% and for dirty ones.

4.2 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 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*

[7] 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 patents over each.

used to prevent environmental pollution'. In both cases, answers are given on a 5-point scale.

Because taxes pertain to public policy more directly than to consumer 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.* We code all answers so that higher values mean more pro-environmental attitudes (see Appendix C). 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 environmental willingness-to-pay for 41 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 are using, 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 to US respondents. The prevailing trend from the early 1990s to the beginning of the 2010 decade 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. Although we do not have such recent data for other countries, we hypothesize that this might be a more general trend. Therefore, in the last section, we will forecast what our estimates would 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.

4.3 Competition

Our main country-level indicator is the World Bank's openness measure, defined as (Imports + Exports)/GDP. We also use, for robustness checks, the Product Market Regulation (PMR) indicator from the OECD (Koske et al., 2015), which is available only for a subset of countries and years. Both are again translated into z-scores.

To compute a more direct firm-level measure, we rely on a Lerner-Index-style approach, derived from a structural production-function regression. Compared to a standard Lerner Index, it allows for non-constant returns to scale and quasi-fixed production factors (see Appendix C). This approach requires using balance-sheet data from OR-

BIS, and the merge with our patent data is only possible for a subset of firms. This firm-level measure for the automobile sector displays much less heterogeneity in trends than country-level indicators: most automobile firms experienced a *reduction in market power* during that time period (see Appendix, Figure A2).

4.4 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, and population from the IMF's World Economic Outlook. In some robustness checks we also include 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.

4.5 Patent portfolio weights

Our benchmark definition of country-firm weights $\omega_{c,t}$ is the share of a firm's patents filed in each country between 1950 and 1990. The denominator includes not only clean or dirty patents, nor automobile-related ones, but include all patents of the firm in the relevant countries. Our other weights definitions yield similar results. Whatever the definition, the US has the largest weight, on average between 7 and 16%, followed by Germany, Japan, the UK and France.

5 Empirical results

Table 1 reports our benchmark results, with all magnitudes expressed as z-scores. Panel A displays the main effects of environmental values and competition on the direction of innovation. Panel B adds an interaction between values and competition. Column 1 shows the main outcome of interest, namely the growth rate of clean innovation relative to dirty ones; Columns 2 and 3 report the effects on both types separately. Finally, in Columns 4 and 5, the outcomes are respectively grey innovation and all the "other" car-related innovations not classified as either clean, dirty or grey.

We see that greener consumer values push innovation in the clean direction, primarily by reducing the growth rate of dirty patents. Competition has a strong significant positive effect on *both* types of innovation; although it is stronger for clean than dirty, the difference is not significant. Panel B shows that the interaction between values and competition has a significant positive effect on the growth rate of clean innovations, both in absolute terms (Column 2) and relative to dirty innovations (Column 1).

Thus, a one-standard-deviation increase in exposure to pro-environmental values is associated with a growth rate of clean patents 14% higher than that of dirty patents, at the mean level of competition. This effect increases to 17% 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.

Panel C reproduces Panel B, but controlling for environmental policies. The EPS index is only available for 25 countries, so we recompute the weights with this smaller set. As was already the case in Aghion et al. (2016), environmental policies do not appear to be a significant determinant of innovations: the coefficient on EPS is never significant. Including it makes competition's effect on all types of innovations besides grey ones become insignificant, however.

Table 2 examines the results' robustness. Panel A explores various weights definitions. In Column 1, we incorporate pre-period GDP's to the weights, based on the idea that large countries matter more. Following Dechezleprêtre et al. (2019), we use $(GDP)^{.35}$: if larger markets attract more firms, each firms' share will decline with country size.[8] The weights become:

$$\omega_{j,c} = \frac{\omega_{j,c} \times GDP^{.35}_{c,pre-period}}{\sum_{c=1}^{41} \omega_{j,c} \times GDP^{.35}_{c,pre-period}}. \tag{13}$$

More than half of 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. In Column 2, we do not do this transformation. In Column 3, we drop firms that did not patent in the pre-period. In Column 4, we assign them, for each country, the average weight among firms that *did* patent in the pre-period. Results are very consistent across specifications, as well as when restricting attention to only car-related patents, or to those with at least one citation (available upon request).

Panel B shows robustness to alternative measures of competition or values. Column

[8] Eaton et al. (2011) estimate an elasticity of firms' average exports to GDP of destination country of 0.35

1 is the benchmark, identical to Column 1 of Table 1, Panel C. In Column 2 we use the "higher tax" question only, instead of our index, to proxy for environmental willingness-to-pay. In Column 3 we use the firm-level Lerner measure of competition, and in Column 4 the OECD Product Market Regulation measure. Results are robust, except in the last specification where the interaction term loses significance.

Panel C shows robustness to alternative treatments of the "grey" and "other" patents, which were dropped in our baseline. "Grey" refers to innovations that make the ICE cleaner, hence are neither perfectly clean nor totally dirty; "other" are innovations that arguably could be classified as "dirty". In Column 1, "grey" is included in the "dirty" category, in Column 3 with the "clean" one instead. In Column 2, dirty consists of dirty, grey and other patents while in Column 4 it consists of dirty and other. These changes do not affect results much, except when "grey" is classified as "clean".

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. Competition per se fosters both types of innovation, with a small but insignificant advantage towards cleaner ones.

6 Accounting and counterfactual exercises

To examine how economically relevant the effects estimated are, we use our fitted model (Table 1, Panel B) to conduct both retrospective and prospective simulations.

Table 3 (Panel A, Column 1) shows that, between 1998-2002 and 2008-2012, the share of clean innovations increased by 23.4 percentage points, while that of dirty innovations decreased by 20. *How can this be reconciled* with the previously mentioned fact that citizens in our sample countries generally became *less* concerned with environmental priorities between 2000 and 2010?

The answer is twofold. First, over that period there was a quintupling of tax-inclusive fuel prices, which naturally induces substitution towards cleaner vehicles. More interestingly, 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 1.0 percentage point, the grey one by 1.5, and the dirty one would have risen by 2.4. Because of correlation between firms's 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: Column 2 shows that, evaluated at the (patent-weighted) average level of competition $\bar{C}$, it equals $-2.2, 1.2$ and 0.8 points respectively. Column 3 reveals, however, that *values decreased less, or increased more,* in countries with relatively *stronger competition*, and especially so for the firms that account for the most patenting: this *interaction* effect dominates the previous one, with contributions of $2.9, 1.9$, and -4.9 points respectively. The actual impact of changes in values was thus *positive* for the "greenness" of R&D (e.g., $2.9 - 2.2 = 0.7$ instead of -1.0 for the clean share), in spite of their average decline.

Similar but smaller compositional effects are present for changes in competition, ΔC_j. On average, and evaluated at the average level of environmental values $\bar{V}$, they account for a rise of 3.7 points for clean patents and a decline of 5.2 for dirty ones (Column 3); their correlation with environmental concerns augments these numbers by 0.4 and -0.3 respectively (Column 5). When all linear and nonlinear effects of preferences and competition are included (Column 7), the changes add up to $+4.4$ for clean and -5.5 for dirty. Column 8, finally, incorporates variations in oil prices; the grand total ($+29$ for clean and -26.7 for dirty) exceed the observed changes, meaning that other factors (e.g., the Great Recession) must have dampened the shift towards clean.

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 prosocial values there was a decrease of 0.74 standard deviations, and we now simulate a *uniform* increase of the same size; for competition there was an increase of 0.91 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 $2.8 - 1.0 = 1.8$ points, while that in competition would raise it by $1.2 + 0.9 = 2.1$. Their combined effect is a 4.3 point increase, which is equivalent to that of a 34% world-wide rise in fuel prices. Given the often dramatic public reactions to even moderate attempts to increase fuel prices (e.g. the French "Gilet Jaunes"), this suggests that grassroots and public campaigns to promote citizens' environmental responsibility could be a viable alternative policy option, especially when combined with more competitive markets.

7 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. Our results are robust to various indicators for environmental values, policies, and product market competition.

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. When further leveraged by strong competition between firms, moreover, such prosocial motivations can actually "move markets", even at the upstream stage of product research and development.

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.

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.

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.

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.

I. Koske, I. Wanner, R. Bitetti, and O. Barbiero. The 2013 update of the OECD's database on product market regulation: Policy insights for OECD and non-OECD countries. Mar. 2015. Publisher: OECD.

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 and N. H. 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

VARIABLES	(1) log (1+ #clean) - log (1+ #dirty)	(2) log (1+ #clean)	(3) log (1+ #dirty)	(4) log (1+ #grey)	(5) log (1+ #other)
		Panel A: Values and Competition main effects			
Values	0.107***	0.00473	-0.103***	-0.0191	-0.136***
	(0.0211)	(0.0191)	(0.0179)	(0.0157)	(0.0239)
Competition	0.269	0.514***	0.246*	0.381***	0.555***
	(0.166)	(0.144)	(0.128)	(0.108)	(0.162)
Log fuel price	0.965***	0.784***	-0.181	-0.0386	0.603***
	(0.156)	(0.138)	(0.127)	(0.114)	(0.161)
Observations	17,124	17,124	17,124	17,124	17,124
R-squared	0.122	0.179	0.026	0.052	0.050
Number of firms	8,562	8,562	8,562	8,562	8,562
		Panel B: Adding interaction term between Values and Competition			
Values	0.141***	0.0350	-0.106***	-0.0276	-0.0859***
	(0.0270)	(0.0230)	(0.0225)	(0.0200)	(0.0289)
Competition	0.167	0.422***	0.255**	0.406***	0.403**
	(0.165)	(0.140)	(0.126)	(0.107)	(0.161)
Values×Comp	0.0296**	0.0268**	-0.00278	-0.00750	0.0441***
	(0.0136)	(0.0116)	(0.0110)	(0.00994)	(0.0139)
Log fuel price	0.596***	0.450***	-0.146	0.0549	0.0527
	(0.171)	(0.149)	(0.154)	(0.140)	(0.215)
Observations	17,124	17,124	17,124	17,124	17,124
R-squared	0.123	0.180	0.026	0.052	0.053
Number of firms	8,562	8,562	8,562	8,562	8,562
		Panel C: Robustness to controlling for environmental policies			
Values	0.109***	0.00174	-0.107***	-0.0474***	-0.112***
	(0.0242)	(0.0197)	(0.0213)	(0.0181)	(0.0294)
Competition	-0.0123	0.265	0.277	0.435***	0.378
	(0.215)	(0.174)	(0.201)	(0.161)	(0.264)
ValuesXComp	0.0224**	0.0231**	0.000670	-0.00718	0.0376***
	(0.0106)	(0.00924)	(0.00879)	(0.00793)	(0.0116)
Log fuel price	0.559***	0.245*	-0.314**	-0.0648	-0.234
	(0.167)	(0.144)	(0.148)	(0.130)	(0.210)
EPS	0.235	0.161	-0.0743	0.0615	-0.237
	(0.146)	(0.120)	(0.138)	(0.111)	(0.198)
Observations	17,124	17,124	17,124	17,124	17,124
R-squared	0.121	0.180	0.025	0.052	0.050
Number of firms	8,562	8,562	8,562	8,562	8,562

Note: All variables are normalized to z-scores. In panel A and B we use 41 countries to compute the values and competition exposure measures. In panel C, we use only 25 countries, the ones for which the Environmental Policy Stringency (EPS) index is available. Besides the coefficients shown, all specifications control for log of population and log of GDP and include firm fixed effects and a period fixed effect. Standard errors are clustered at the firm level.

Table 2: The effects of Values and Competition on the direction of innovation

	(1)	(2)	(3)	(4)
VARIABLES	log (1+ #clean) - log (1+ #dirty)			
	Panel A: Robustness to different weights			
Values	0.117***	0.0418**	0.168***	0.266***
	(0.0247)	(0.0177)	(0.0314)	(0.0663)
Competition	0.181	0.0747	0.173	0.194
	(0.126)	(0.0703)	(0.181)	(0.428)
Values×Competition	0.0391***	0.0525***	0.0430**	0.0563***
	(0.0120)	(0.0130)	(0.0191)	(0.0190)
Log fuel price	0.427***	0.0998	0.643***	0.836**
	((0.128)	(0.0647)	(0.186)	(0.369)
Observations	17,124	17,124	6,704	17,124
R-squared	0.120	0.102	0.176	0.122
Number of firms	8,562	8,562	3,352	8,562
	Panel B: Robustness to different values and competition measures			
Values	0.109***	0.153***	0.177***	0.102***
	(0.0242)	(0.0500)	(0.0421)	(0.0250)
Competition	-0.0123	0.283	0.00387	0.00949
	(0.215)	(0.223)	(0.0319)	(0.124)
Values×Competition	0.0224**	0.0546**	0.0658*	0.0162
	(0.0106)	(0.0217)	(0.0352)	(0.0161)
Log fuel price	0.559***	0.402	1.416*	0.722***
	(0.167)	(0.269)	(0.731)	(0.258)
EPS	0.235	0.398***	0.124	0.328**
	(0.146)	(0.150)	(0.256)	(0.148)
Competition measure	World Bank	World Bank	Lerner	OECD
Values measure	Index	Higher Tax	Index	Index
Observations	17,124	17,124	2,706	17,124
R-squared	0.121	0.120	0.199	0.120
Number of firms	8,562	8,562	1,854	8,562
	Panel C: Robustness to different treatments of ”other” and ”grey”			
Values	0.175***	0.188***	0.0590**	0.176***
	(0.0283)	(0.0205)	(0.0245)	(0.0198)
Competition	-0.210	-0.210	0.498***	-0.111
	(0.182)	(0.140)	(0.170)	(0.132)
ValuesXCompetition	0.0407***	0.0177**	0.00756	0.0125
	(0.0142)	(0.00787)	(0.0118)	(0.00765)
Log fuel price	0.413**	-0.0456	0.645***	0.0291
	(0.196)	(0.164)	(0.160)	(0.160)
Clean	clean	clean	clean + grey	clean
Dirty	dirty + grey	dirty+ grey + other	dirty	dirty + other
Observations	17,124	49,482	17,124	49,482
R-squared	0.070	0.051	0.149	0.050
Number of firms	8,562	24,741	8,562	24,741

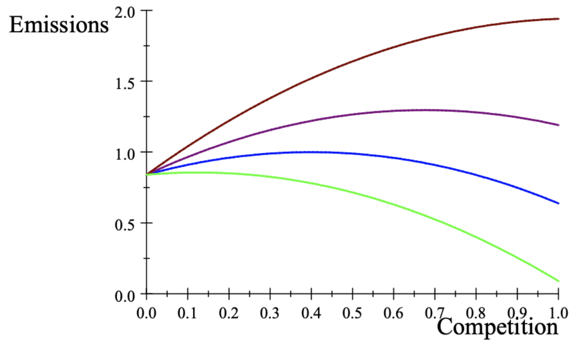
Note: All variables are normalized to z-scores. Besides the coefficients shown, all specifications control for log of population and log of GDP and include firm fixed effects and a period fixed effect.

Table 3: Historical and Prospective Counterfactuals

Share change	(1) Actual $\triangledown$	(2) $\triangleleft$— $(\alpha+\gamma\bar{C})$ $\times\Delta V$	(3) $\gamma\left(C-\bar{C}\right)$ $\times\Delta V$	(4) $\left(\beta+\gamma\bar{V}\right)$ $\times\Delta C$	(5) Due To $\gamma\left(V-\bar{V}\right)$ $\times\Delta C$	(6) $\gamma\Delta V$ $\times\Delta C$	(7) $\Delta V, \Delta C$	(8) $\Delta V, \Delta C,$ ΔP	(9) —$\triangleright$ Other
				Panel A: Historical					
Clean:	23.8	-2.2	3.0	2.9	1.2	-0.5	4.4	32.5	-8.7
Grey:	-3.2	1.2	2.0	1.9	-0.8	0.2	1.1	-5.9	2.7
Dirty:	-20.7	0.8	-1.2	-4.9	-0.5	0.1	-5.5	-26.7	6.0
				Panel B: Prospective					
Clean:		2.8	-1.0	1.2	0.9	0.7	4.3	-	-
Equiv. $\Delta P/P$ (%)		21	0	9	6	5	34	-	-

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. See Appendix B for details.

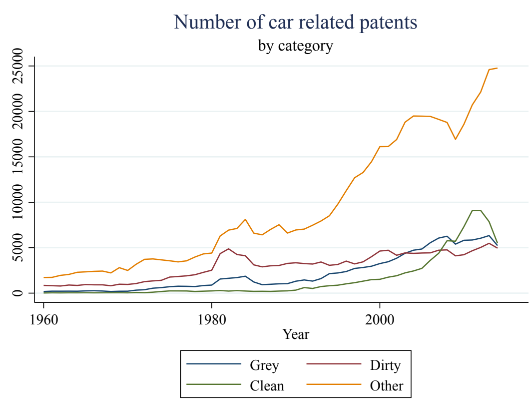
Figure 1: Effect of competition and social values on pollution



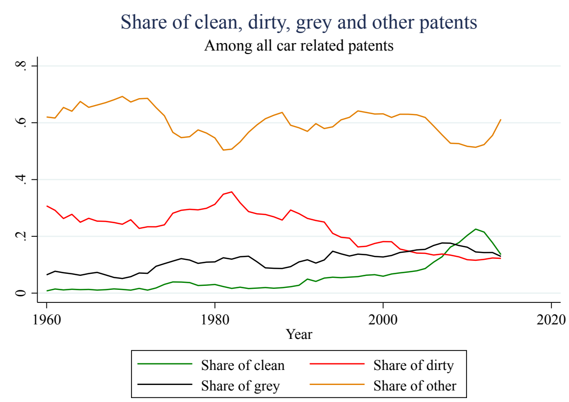
Polluting emissions as a function of market competition, as prosocial attitudes vary from lowest to highest (top to bottom curves)

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 for more details.

ONLINE APPENDIX

Appendix A: Proofs

Proof or Proposition 2. For all $\kappa > \kappa_{1,}$ so that z is interior, 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, 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 $\hat{\Delta}_Z(\gamma, \delta) \in (1/2, 1)$ 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

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

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

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

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

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

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

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

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

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

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 $\partial^2 U/\partial\Delta\partial\delta > 0$.

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:

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

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 (12)as

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

where, for each firm j and time, PAT_{jt} is the number of patents (families) of a given type (clean, dirty, etc.), V_{jt} and C_{jt} are its (average) degrees of exposure to prosocial values and competition respectively, and F_{jt} collects all other explanatory variables, such as oil prices, firm and period fixed effects, etc. There is one such estimation for each patent type, but for simplicity we abstain here from indexing the regression coefficients by "clean," "dirty", etc.

Denoting $\Delta X_{j_t} = X_{jt} - X_{j\tau}$ 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

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

where (omitting time subscripts to lighten the notation):

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

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 total of 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_{jt}? 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.[9] 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 4, 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. As seen in Tables B.1 and B.2, between $\tau = 2002$ and

[9] We use the patent levels corresponding to the "clean" category. Using those for "dirty" or "grey" instead, or using each one for the corresponding version of (B.2)-(B.4), leads to broadly similar results.

$t = 2012$, firms' ΔV_j's were overall sightly positively correlated with their $C_j - \bar{C}$'s, but strongly so where the ΔV_j's were most important (top percentile), and especially among firms most active in patenting activity. The weighted covariance of the two variables is thus 1.63 (versus an unweighted one of 0.002), almost twice as large as the weighted-mean effect of -0.91. That is why, in Panel A of Table 3, Column 3 shows positive contributions of changing values to clean and negative to dirty, which swamp the adverse mean effects from Column 2.

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,* $\hat{\gamma}(\Delta V_{jt} \times \Delta C_{jt})$. Column 8, finally, simulates the full fitted model (B.1)-(B.2), in which the $\hat{\varphi}\Delta F_{jt}$'s include in particular includes 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 ΔV_{jt}'s and ΔC_{jt}'s are taken to be *uniform* across firms, equal respectively to 0.74 and 0.86 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.
$\Delta Values$	-0.742	0.766	-2.357	-0.911	2.227	-0.909	1.250
$\Delta Comp$	0.861	0.160	0.347	0.915	1.145	0.760	0.223
$(Comp - \overline{Comp}) \times \Delta Values$	0.002	1.407	-2.125	-0.379	6.747	1.631	3.117
$\left(Values - \overline{Values}\right) \times \Delta Comp$	-0.062	0.722	-2.635	-0.124	1.908	0.395	1.229
$\Delta Values \times \Delta Comp$	-0.609	0.896	-1.38	-0.834	2.389	-0.542	1.393
$\Delta log(FuelPrice)$	1.698	0.202	1.601	1.601	2.381	1.963	0.343

Note: Values and Competition are measured as in Table 1, Panel B. Patent weighting is defined in equation B.4, using firms' clean patent levels in 2002.

Table B.2: Correlations between key variables (2008-2012)

	Clean	Grey	Dirty	Values	Competition		
Clean	1						
Grey	0.869	1					
Dirty	0.443	0.659	1				
Values	0.106	0.084	0.017	1			
Competition	-0.154	-0.154	-0.108	-0.604	1		
ΔValues	-.028	0.015	0.103	-0.489	0.003	1	
ΔCompetition	-0.81	-0.066	-0.013	-0.403	0.680	0.246	1

Note: Clean, Grey and Dirty correspond here to (one plus) each firms' number of patents in each category, in 2002. The measures of Values and Competition used are the same as in Table 1, Panel B.

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.[10]

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

Answers to the ISSP question *"How willing would you be to pay much higher taxes in order to protect the environment?"* vary from 1 ('very willing') to 5 ('very unwilling') 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. Answers to the two additional questions we use from WVS and ISSP are again reverse coded to ensure consistency. 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.

[10] 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`.

C3. OECD PMR indicator

The OECD Product Market Regulation (PMR) indicator is a comprehensive variable that aggregates responses from a questionnaire of over 700 questions, falling into three main areas: state control, barriers to entrepreneurship, and barriers to trade and investment. We use it as robustness and not as our main measure, because it does not cover as many countries and years as the World Bank index. The two measures have a correlation of 0.3. Indeed, some countries rank very differently along them, like the US which is among the least open according to the World Bank, but the most competitive besides Great Britain according to the OECD.

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_{it} and labor L_{it} as flexible factors, and capital K_{it} a quasi-fixed production factor. A firm's (log) revenue (R_{it}) growth can then be written as

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

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

$$s_{Mit} = \frac{\alpha_{Mit}}{\mu_{it}}, \tag{C.2}$$

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

$$\alpha_{Mit} = \alpha_M + \alpha_{KM} k_{it} + \alpha_{LM} l_{it} + \alpha_{MM} m_{it}. \tag{C.3}$$

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

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

where

$$\Xi_{it} \equiv \frac{\Delta r_{it} - \frac{\lambda}{\bar{\mu}_{it}} + \bar{s}_{Mit}\left(\Delta m_{it} - \Delta k_{it}\right) + \bar{s}_{Lit}\left(\Delta l_{it} - \Delta k_{it}\right)}{\bar{s}_{Mit}}.$$

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 $\Delta\omega_{it}$ follows an AR(1) process, $\omega_{it} = \rho\omega_{it-1} + \eta_{it}$ where η_{it} is iid, we can write

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

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

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

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

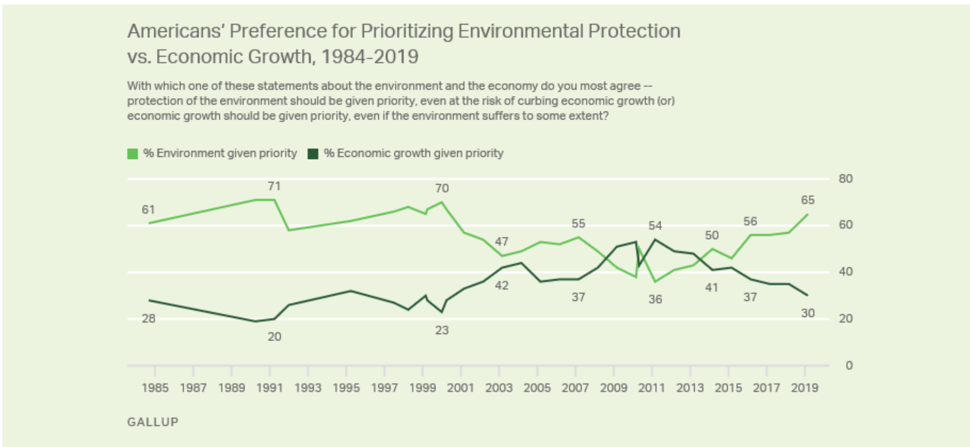
$$\frac{\widehat{\lambda}}{\mu_{it}} = s_{Mit}\left(\frac{\widehat{\alpha_{Mit}}}{\lambda}\right)^{-1}, \tag{C.5}$$

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 $\alpha_{Mit} = \alpha_M$. 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.

Appendix Figures

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

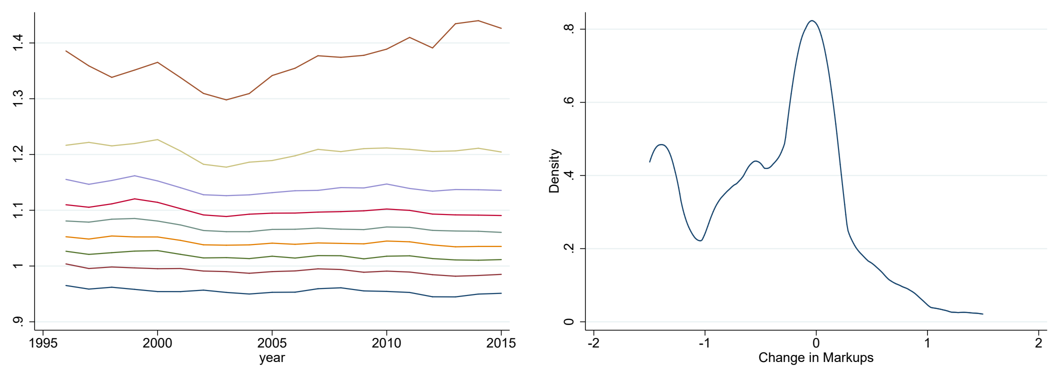


Source: "Preference for Environment Over Economy Largest Since 2000", by Lydia Saad for Gallup News, April 2019

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.