Essays on the Economics of Technological Change and the Environment

Eugenie Dugoua

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ABSTRACT

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Technological change bears the promise of addressing environmental problems without reneging on economic development. However, taping its full potential requires an understanding of its drivers and barriers. The three chapters of this dissertation are a modest attempt at casting light on some of the factors that can foster technological change towards more environmental-friendly technologies. In Chapter One, I provide the first quantitative evidence that the Montreal Protocol, and its following amendments to protect the ozone layer, triggered a large increase in research and innovation on alternatives to ozone-depleting molecules. To do this, I use the full text of patents and scientific articles and implement a difference-in-differences strategy and a synthetic control method. To compare molecules' chemical and industrial characteristics, I construct descriptive variables by applying machine learning techniques to the documents' text. In Chapter Two, I investigate barriers to adopting solar lanterns in the context of rural Indian households. I design and implement a randomized controlled trial on people's willingness to pay for such lanterns, and find that, despite the relative simplicity of the product, information barriers to adopting solar lanterns remain high. Chapter Three theoretically investigates firm-level barriers to green technological change. I outline a mechanism that explains why coordination at the industry level might be necessary. I argue that radical innovations (such as electric cars) require complementary innovations in interdependent components, and show that, when technological change requires investment by both suppliers and producers, coordination within an industry is needed and can be difficult to obtain.

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"C'est pourquoi fault ouvrir le livre et soigneusement peser ce que y est déduict [...]. Puis, par curieuse leçon et méditation fréquente, rompre l'os, et sugcer la substantificque moelle, [...]".

"It becomes you to be wise to smell, feel, and have in estimation these fair books [...] Then you must, by a curious reading and frequent meditation, break the bone and suck out the substantific marrow, [...]".

François Rabelais, *Gargantua* (1534)

Accordingly, I dedicate this work to all bone breakers and marrow extractors, who thrive on seeking out substantific knowledge. And never with the guarantee of success.

Introduction

Approach

Technology has many implications for how societies interact with the natural environment. On one hand, the type and scale of technological use cause damages to the planet. On the other, *changes* in technologies bear the promise of addressing environmental problems without reneging on economic development. But taping the full potential of technological change requires to understand its drivers and barriers. My interests, therefore, lie primarily in studying how institutions and policies influence science, innovation, and technological change so that economic development can be sustainable for the environment and societies. To realize this research agenda, I apply traditional methods from the economics discipline, including theoretical modeling, econometric analysis, and field experiments. I also leverage more recently developed tools such as machine learning techniques for text analysis. I purposefully seeked training and practice in these different methodologies with the aim of not being limited method-wide in the type of questions I wish to carefully examine.

My research interests can be categorized into three central themes. The first focuses on the effect of environmental regulations and international agreements on science and innovation concerning environmental-friendly technologies. In Chapter 1 of this dissertation, I examine the particular case of the Montreal Protocol to protect the ozone layer. My interest here was spurred by realizing that solving environmental problems such as climate change requires both cooperation from many different countries and extensive technological change. History provides few examples for us to understand both conceptually and practically how such technological change can take place. The response to the threatened depletion of the ozone layer is regularly cited as the most environmentally successful instance and, as a result, is frequently debated as a model for resolving the issue of climate change. These debates often center around similarities and differences of the ozone and climate cases along economic, environmental, technological, and political dimensions. However, I took from these discussion an absence of understanding of the dynamics of innovation involved in dealing with the ozone crisis. I, consequenty, undertook to build a foundation to achieve this understanding by collecting data and using innovative empirical methods.

The second central theme in my research interests concerns technological change in developing countries and in particular energy poverty. Throughout my graduate studies, I have discerned overlap in thinking about the barriers to moving up the development ladder and those to moving away from polluting technologies. Both cases involve massive technological change. Here my primary research interests focus on how developing countries can more effectively fulfill their energy needs without requiring fossil fuels. To carry out this work, I am studying socioeconomic barriers to electrification and the diffusion of environmental-friendly technologies. Chapter 2 of this dissertation focuses on barriers to diffusion of solar lanterns in rural India. Finally, the third theme central to my research interests focuses on challenges to green technological transitions *at the firm level*, and Chapter 3 of this dissertation looks at the role supply chain networks on firms' ability to innovate.

Chapter Summaries

Chapter 1:

International Environmental Agreements and Directed Technological Change: Evidence from the Ozone Regime

Can international environmental agreements induce innovation on green technologies? It is possible that international negotiations succeed only once technological solutions are available. In this case, agreements would help diffuse such technologies rather than fostering their development. I provide the first quantitative evidence that the Montreal Protocol, and its following amendments to protect the ozone layer, triggered a large increase in research and innovation on alternatives to ozone-depleting molecules. To do this, I use the full text of patents and scientific articles to construct new panel data of the yearly number of published documents about these molecules. I implement a difference-in-differences strategy (DiD) and a synthetic control method (SCM) using hazardous air pollutants as control units. To compare molecules' chemical and industrial characteristics, I construct descriptive variables by applying machine learning techniques to the documents' text. The SCM estimates that the post-Montreal regime caused a 144% increase in patents and a 189% increase in articles mentioning substitutes to ozone-depleting substances; the DiD yields comparable estimates. These results challenge the view that agreements foster technological diffusion without affecting much of the dynamics of innovation. Agreements can thus encourage the development of green technologies, which importantly suggests they should be negotiated as early as possible if we hope to solve global environmental problems.

Chapter 2:

Passive Learning and Incentivized Communication: A Randomized Controlled Trial in India

Joint work with Yonas Alem.

In order to understand the extent of the information barrier to adoption of a household technology, we designed a randomized controlled trial on willingness to pay (WTP) for solar lanterns in India. We gave high quality solar lanterns to randomly selected 'seed' households in a non-electrified region of the state of Uttar Pradesh. Three friends of the seed household were randomly assigned to one of the following three groups: control, passive learning and incentivized communication. We elicit WTP from the control group when the seed receives the solar lantern. We elicit WTP from the friends in the passive learning and incentivized communication groups thirty days after the seed receives the solar lantern. We show that passive learning increases WTP by 90% and incentivized communication by 145% relative to the control group. We also show that learning from others is the mechanism that drives the observed WTP by peers.

Chapter 3:

A Theoretical Model of Technological Change in Industrial Networks and Implications for a Green Technological Transition

Joint work with Marion Dumas.

The literature on technological change has studied several types of positive externalities leading to sub-optimal levels of development and adoption of technologies. In this paper, we suggest another type of positive externality: supplier network externality. In this case, the cost to one producer of producing a new technology may depend on how many other producers are deploying similar technologies. Specifically, production costs decrease as several producers source similar inputs from shared suppliers, generating economies of scope. To illustrate the mechanism, we develop a stylized model of two producers with a shared supplier. We introduce the possibility that producers innovate in incompatible ways requiring very different inputs from the supplier. This triggers a loss in economies of scope and reduces the equilibrium level of innovation. We argue that the model has implications for a green technological transition. In this case, lock-in situations can lead to market failures since green innovations are socially desirable. We use supply-chain relationship data to show that our model is of particular relevance to the car manufacturing industry and, we highlight how our results help unify findings from several case studies.

Future Research Directions

In the future, I intend to continue some of the work presented in this dissertation, as well as start new projects related to the three main themes described earlier.

I intend to further the work presented in Chapter 1 by investigating to what extent the strengthening evidence of the urgency to phase-out CFCs, mostly through the ozone hole "discovery", might have directly incentivized firms to develop on CFC substitutes. I will attempt at identifying such effect by leveraging variation in the timing of regulation of different molecules. Specifically, two molecules (carbon tetrachloride and methyl chloroform) were recognized as strong ozone-depleting substances but were not included in the 1987 agreement. Instead, they became regulated in 1990. I intend to analyze trends in science and innovation for substitutes to carbon tetrachloride and methyl chloroform to infer whether the ozone hole "discovery" might have directly affected firms' behavior. On a different note, I also intend to further exploit the richness the patent and article data that I collected to paint a more precise picture of the micro-dynamics of the technological change that took place during the ozone crisis. This would imply more analysis at the level of firms and researchers.

I also intend to continue initiated collaborations on the theme of technological change in developing countries and in particular energy poverty. In this context, in prior joint work with Ryan Kennedy and Johannes Urpelainen (Dugoua et al. 2017b), I explored the potential of nighttime lights data for measuring electrification progress. We showed that many measures derived from satellite data are surprisingly accurate for measuring rural electrification and demonstrate how they could be substantially improved by using better GIS maps, basic geoprocessing tools, and particular aggregations of nighttime luminosity. Similarly, in work with Johannes Urpelainen and Ruinan Liu (Dugoua et al. 2017a), I examined who benefited from the recent progress in rural electrification in India. Our findings highlight the importance of socioeconomic barriers to rural electricity access and alleviate concerns that remoteness and population density are crucial obstacles to grid extension. Following on this strand of work, I am part of a team of researchers, including Johannes Urpelainen and Ryan Kennedy, working on an original household survey funded through a MacArthur grant to collect data on sustainable energy use in India. The project will leverage the penetration of devices connected to the Internet and energy monitors to improve the quality and speed of data collection on energy consumption. Consequently, the collected data will provide the most detailed and large-scale mapping of energy access in India to date. This, in turns, will be use to better understand the drivers and barriers of sustainable energy diffusion in India, as well as to customize energy access interventions to meet the needs of different communities.

I also intend to continue the work initiated in Chapter 3 to better understand challenges of technological change at the firm's level. We would like to use data on patents and buyer-supplier relationships to empirically investigate the implications of our theory. We also plan to generalize the model by allowing for more producers and suppliers. Finally, I project to examine interactions between innovation and science in the context of environmental issues. In this research, jointly pursued with Eliott Ash, I will look at whether granting patents on green technologies could stimulate research publications on related environmental topics. It is often argued that the patent system is beneficial since it renders information about inventions public, which, in turn, stimulates the development of new ideas. However, little empirical evidence supports such a theory (Ouellette 2011; Sampat et al. 2015; Walsh et al. 2007; Williams 2017). My research will use exogenous variation in the leniency of patent examiners to identify if patenting has a positive causal effect on generating new scientific knowledge. In this research, I will also use machine learning tools for text analysis to link patent applications to academic articles.

Chapter 1

International Environmental Agreements and Directed Technological Change: Evidence from the Ozone Regime

1.1 Introduction

International environmental agreements, like domestic policies, attempt to mitigate environmental degradation. Agreements, however, are needed when environmental problems run across national borders. In such contexts, individual governments usually lack incentives to create domestic policies, and international cooperation is needed. A large literature has developed to better understand the drivers of environmental-friendly innovation, and many studies show that domestic environmental policies can foster green innovation (Jaffe et al. 2002; Popp et al. 2010). I ask: Can international environmental agreements, like domestic policies, foster innovation? It is possible that they don't: noncooperative game theory suggests that agreements occur when costs to the players are low. Hence, agreements might only occur once technological solutions are readily available, and they might simply contribute to diffusing these technologies, as opposed to fostering the development of new ones.

This paper shows that, on the contrary, agreements can induce innovation and that agreements, therefore, are part of the process of delivering cheaper environmental-friendly technologies. This provides a strong argument for negotiating ambitious agreements as early as possible since technologies are too often the keystone for addressing environmental problems. To make this argument, I provide empirical evidence from the Montreal Protocol and its following amendments. In 1987, at Montreal, high-income countries decided to phase-out chlorofluorocarbons (CFCs) from industrial activities because CFCs were known to destroy the protective layer of ozone molecules in the stratosphere. Technological change unrolled rapidly: within a decade, the production and consumption of CFCs decreased by more than 80%[1]. The protocol is still hailed as one the most successful environmental international agreement and remains a point of reference in policy discussions about global environmental problems.

Despite the large scholarly literature on the topic, the dynamics of innovation in the ozone crisis are still debated. Richard E. Benedick, chief U.S. negotiator at Montreal, claims

[1] My calculations using UNEP data.

the agreement triggered a vast effort in research to find CFC substitutes (Benedick 2009). But others emphasize that CFC substitutes were already available at the time of negotiations (Heal 2016; Sunstein 2007). This paper is not only the first to empirically show that Montreal fostered innovation, but it also quantifies its effect. I do this using a novel molecule-level panel dataset with both a difference-in-differences (DiD) strategy and a synthetic control method (SCM). Additionally, I apply machine learning methods to semantically match documents and measure similarity between molecules.

Successfully developing CFC substitutes did not simply mean identifying chemical structures. Mostly, the set of molecules with greatest potential to be CFC substitute was public knowledge; I compile a list of 14 of such molecules[2] and consider those molecules as treated by the Montreal Protocol. The technological challenge, instead, lied in finding out how such molecules could be used in the myriad of industrial processes that required CFCs, cost-effectively and at a large scale. This meant, first, learning about thermodynamics properties, toxicity profile, and environmental acceptability; I collect scientific articles published in journals indexed by Science Direct between 1970 and 2000 to capture such research effort. Second, new process and formula designs were needed to retrofit installed equipment with the CFC substitutes or to altogether replace it; I collect patents granted by the United States Patent and Trade Office (USPTO) between 1976 and 2000 to track progress on these aspects.

Unfortunately, no preexisting classifications allow me to easily identify which documents relate to CFC substitutes. I, therefore, search the full text of patents and articles for mentions of any of the 14 CFC substitutes[3] and construct a panel dataset where each observation is the number of documents mentioning a given molecule at least once in a given year. Finally,

[2] I used the report published in 1988 by the AFEAS (Alternative Fluorocarbon Environmental Acceptability Study). After the agreement at Montreal, manufacturers were given authorization by anti-thrust authorities to cooperate on some specific areas. The AFEAS publication shared what they knew about the *atmospheric characteristics* of several potential CFC substitutes.

[3] Since molecules usually have many different names[4], I develop an automatic script to collect all possible names from SciFinder, a database of chemical information.

I apply machine techniques to text analysis to construct variables that proxy the scientific and industrial context of the molecules. These variables correspond to the proportion of specific topics present in documents mentioning molecule i. Intuitively, they describe the type of words associated with molecule i.

I begin by estimating the difference before and after the signing of Montreal in the number of documents mentioning CFC substitutes: I find large increases, close to 600% in patents and 200% in articles. Additionally, I find that only very few patents and articles on CFC substitutes are published before 1987, and the trend prior to 1987 ("pre-trend") is remarkably flat. I argue that this is indicative of technological progress not being a key driver of negotiations' success, and that the agreement was little anticipated. To account for potential underlying trends, I compare innovation on CFC substitutes with a control group: I use 171 hazardous air pollutants (HAPs). These molecules can serve as controls because they are unrelated to ozone or to CFCs and, just like CFC substitutes, are used in a diverse range of industrial applications. Importantly, pre-trends in the number of documents mentioning both sets of molecules are comparable. The main DiD estimate indicates that Montreal led to an increase of about 546% and 95% in the number of patents and articles, respectively, between 1987 to 2000. This corresponds to average annual increases of about 390 patents and 47 articles. The estimates are reduced but remain economically and statistically significant when controlling for lags and topic proportions.

Since one patent or article can often mention several CFC substitutes, the observations used in the DiD design (14 CFC substitutes) are not independent. Another approach, therefore, consists in considering them in aggregate, as one treated molecule. To estimate a treatment effect on such "aggregate CFC substitute", I use an SCM (Abadie et al. 2010, 2015), a method particularly suited for estimating treatment effect of interventions affecting aggregate quantities. To do this, the SCM constructs a control unit by using a weighted average of control molecules. The method chooses the weights so that the synthetic control unit reproduces most closely the log count path of the outcome variable in the pretreatment periods. I also use weights chosen so that the synthetic control resembles the treated unit along topic proportions; this helps obtain a control unit that resembles CFC substitutes along chemical and industrial dimensions.

The average treatment effect using the SCM indicates the Montreal protocol lead to an increase of about 144% in the number of patents mentioning the CFC substitutes, corresponding to about 117 additional patents per year over the study time period after 1987. This yields a lower estimate than the DiD strategy, indicating that the control constructed in SCM provides a more conservative comparison. For articles, on the other hand, results are similar to the DiD. I find an average treatment effect close to a 190% increase in the number of articles, which corresponds to about 43 additional articles per year after 1987. To assess the statistical significance of these results, I follow the placebo tests method suggested by Abadie et al. (2010, 2015). I find treatment effects are significant at the 99% level. In addition, the increase in the number of documents mentioning CFC substitutes becomes statistically significant as from 1990, three years after the agreement was signed. This lag might correspond to the time it organizationally and professionally takes to redirect research towards CFC substitutes and to have patents and articles published (Popp 2002).

These results indicate that the post-Montreal ozone regime caused the development of CFC substitutes. This finding is robust to considering citation-weighted document counts; indeed, the most cited patents and articles on CFC substitutes were published after Montreal. Additionally, one hypothesis is that manufacturers kept their CFC substitutes secret, and Montreal simply created a world market for them. If that were true, we would observe a sudden increase in patents in the few months following the treaty signature. I show that this is not the case both for all patent assignees as well as for the biggest two, Du Pont and Dow Chemical. Additionally, I find that these results are robust to dropping patents and articles with only few mentions of CFC substitutes (e.g. keeping documents with at least three occurrences of a molecule name).

This paper contributes to the literature on directed technological change in the context of environmental issues (Acemoglu 2002; Jaffe et al. 2002; Popp 2010a). Many papers have explored the relationship between domestic environmental regulations and innovation (e.g., Aghion et al. (2016), Calel et al. (2016), and Jaffe et al. (1997)). My paper is most similar to Dekker et al. (2012) in that it investigates the causal effect of an international agreement[5]. However, instead of focusing only on patenting, I also analyze trends in scientific articles. Importantly, while scholars have thoroughly investigated the diplomatic and game theoretic aspects of the ozone crisis (Barrett 2003; Benedick 2009; Murdoch et al. 2009; Parson 2003; Wagner 2009), no quantitative analysis of the dynamics of innovation during the crisis has been carried out. This is despite the economics, science, and politics of ozone serving as an anchor point for our understanding and beliefs about the role of diplomacy, agreements, and technologies in solving environmental issues, especially climate change (Barrett 1999; Sunstein 2007). This paper thus complements the literature on Montreal by showing and quantifying its effect on science and innovation. When solutions to environmental problems are plagued with technological uncertainties or high price tags, decision-makers are incentivized to adopt a "wait-and-see" strategy: wait for proven new technologies, then negotiate an agreement. By showing that agreements can encourage the development of green technologies, this paper suggests they should be negotiated as early as possible if we hope to solve global environmental problems.

The following section 1.2 summarizes the literature on directed technological change and its relationship to the environment and provides further information on the ozone crisis and the Montreal Protocol. I describe the data in section 1.3 and the empirical strategies and main results in section 1.4. I focus on the SCM in section 1.5, and conclude in section 3.4.

[5]Dekker et al. (2012) focus on the signing of the Helsinki and Oslo protocol as part of the Convention on Long-Range Transboundary Air Pollution

1.2 Directed Technological Change and the Ozone Layer

Directed Technological Change and the Environment

The relationship between technological change and the environment has been drawing more interest, particularly since the 1990s. On the one hand, technical change affects the intensity of environmental impacts. On the other, there is the growing recognition that environmental policies create new types of incentives and constraints possibly affecting the direction of technological change. The concept of *directed technological change* goes back to 1936: under the "induced innovation" hypothesis, Hicks (1932) stated that innovations are biased towards high priced factors so to make their use more efficient or to substitute them. In the past two decades, the concept has reappeared under the phrase "directed technical change" (Acemoglu 1998) encompassing not just price effects, but also market size and regulatory effects[6].

In the environmental context, the direction of innovation is particularly important. The usual technology policy (e.g., public funding for research and development activities or intellectual property regimes) attempts to deal with knowledge market failures by fostering the rate of innovation and diffusion of new technologies. But it does so in a direction-blind way. As a result, a large literature has developed at the intersection of environmental and technology policy to better understand how and to what extent technical change could be directed (Jaffe et al. 2002; Popp 2010a; Popp et al. 2010). In fact, we can think of environmental regulations as modifying the shadow prices of environmental inputs which, as the induced innovation hypothesis suggests, induces innovation in non-polluting directions. This is specifically discussed by Newell et al. (1999) who generalized the concept of induced

[6]The phrase's popularity took off after Daron Acemoglu's 1998 model showing that an increase in skilled labor force can induce skill-biased technological change through a market size effect that fosters the development of innovations complementary to the abundant factor, in that case, skills (Acemoglu 1998). In another paper, Acemoglu (2002) presents a model where the direction of technological change is influenced by both scarce factors (through prices) and abundant factors (through market size).

innovation to include inducement by regulations.

The literature initially focused on the impact of environmental regulations on business competitiveness (Ambec et al. 2013; Porter 1991; Porter et al. 1995a,b) and then later on patenting activities and R&D spendings; scholars found strong evidence that regulations have an important influence on environmental-friendly innovations (Brunel 2015; Brunnermeier et al. 2003; Jaffe et al. 1997; Johnstone et al. 2010, 2012; Lanjouw et al. 1996; Nesta et al. 2014; Popp 2005; Vollebergh 2007). For example, Popp (2006) finds significant increases in patents pertaining to sulfur dioxide and nitrogen oxides emissions reduction in response to the passage of environmental regulations in the United States, Japan, and Germany. More recently, Calel et al. (2016) show that the European Union Emissions Trading System increased patenting related to low-carbon technologies by about 10%, while not crowding out other technologies. Although many studies investigate the effect of international environmental agreements on pollution outcomes (Aichele et al. 2011; Finus et al. 2003; Kellenberg et al. 2014), they seldom look at the impact on science and innovation. One exception is Dekker et al. (2012) who show increased patenting activity for countries signatories of the Convention on Long-Range Transboundary Air Pollution.

A Brief History of the Ozone Crisis

The story of the ozone crisis began in 1974 when two chemists published an article in which they laid out the theoretical possibility that ozone molecules could be broken down in the stratosphere by chlorofluorocarbons (CFCs) (Molina et al. 1974)[7]. Even though the potentially harmful effects of a thinner ozone layer were not well studied, it was clear that more UV light would cause more skin cancers, eye cataracts and a likely loss in fishery and agriculture productivity (Miller et al. 1986). CFCs, the main molecules responsible for depleting ozone, had become important molecules for industrial activities due to their

[7] In 1995, Mario J. Molina and F. Sherwood Rowland, together with Paul J. Crutzen, were awarded the Nobel Prize in Chemistry “for their work in atmospheric chemistry, particularly concerning the formation and decomposition of ozone”

chemical properties: they are unusually stable, nonflammable, nontoxic and noncorrosive[8]. This makes them ideal molecules for manufacturing many consumer goods. And, best of all, they were cheap to produce. The use of CFCs spread over five different sectors: foams, refrigeration and air-conditioning, aerosols, fire protection and solvents[9].

In September 1987, industrialized countries agreed to a binding agreement regulating the production and use of CFCs. The approach was flexible with a series of phase-out dates, as opposed to banning altogether the molecules. These phase-out schedules were further consolidated and extended to other molecules in the years that followed[10]. Atmospheric concentrations for most CFCs peaked by 2014 and ozone layer recovery is now expected around 2050 (Hegglin et al. 2015).

The role of the Montreal Protocol in solving the crisis has been intensely discussed (Barrett 1994; Beron et al. 2003; Murdoch et al. 1997; Wagner 2009, 2016). Specifically, Barrett (Barrett 1999) suggested that a key aspect of the protocol was to solve the enforcement problem: Montreal included trade restrictions with non-parties in ozone-depleting substances as well as in products containing those substances. It also included the threat of banning trade in products made using ozone-depleting substances. These trade restrictions effectively acted as a mechanism for free-rider deterrence and leakage prevention. More recently, Wagner (Wagner 2016) provided empirical evidence that these trade measures promoted full participation in the protocol, ensuring its almost-universal ratification. My paper complements this literature by focusing on the quantitative effect of Montreal and its following agreements on science and innovation.

[8] CFCs were first commercially used in 1928 as cooling fluids for refrigerators. They were designed specifically to substitute other refrigerants that were either dangerously toxic or inflammable (Parson 2003).

[9] CFCs are great refrigerants because they vaporize at low temperature and are very energy-efficient coolants. As aerosols, they were used in cosmetics, household products, pharmaceuticals, and cleaners. Finally, their nonreactive property made key products for cleaning microchips and telecommunication equipment

[10] For example, the London amendment, signed in 1990, regulated new chemicals such as carbon tetrachloride and methyl chloroform. In 1995, the parties successfully negotiated phase-out targets for lower-income countries, which were until then exempted from any regulation.

The Role of Technology in the Ozone Crisis

There is no question that if emission reductions were successful, it was thanks to CFC substitutes becoming available. Goods that contained or required CFCs for their production continued to be commercialized, and no air capture system of CFCs was ever designed. But the question of when these CFC substitutes were developed and whether the agreement triggered the bulk of the effort to find them is still debated. Some works have focused specifically on the technological story behind the Montreal Protocol (Glynn 2002; Gonzalez et al. 2015; Le Prestre et al. 1998; Miller et al. 1986; Parson 2003; Taddonio et al. 2012) as well as the reaction of the business community (Falkner 2005; Mulder 2005; Reinhardt et al. 1989a,b; Smith 1998). But, perspectives on the role of innovation remain mixed.

Richard Benedick, head U.S. negotiator at Montreal, argued that the agreement caused a vast effort in research to find CFC substitutes and that qualitative evidence abounds on the dynamics of the innovation process under the Montreal Protocol (Benedick 2009)[11]. Similarly, Edward A. Parson highlights that, although some manufacturers initially started research on potential substitutes in the late 1970s, these efforts quickly came to an end around 1981 (Parson 2003, Chap.3 p.53 and Chap.7 p.173)[12]. As a result, little was known about the toxicity and environmental acceptability of the potential CFC substitutes, whether and how they could be processed at large scale, and whether they would require a redesign of the processes and equipment in the various industries that used CFCs as inputs. Despite both Benedick and Parson arguing that, on the eve of the negotiations, technological uncertainties loomed large, others have taken a different stance. One narrative claims that CFC substitutes

[11] Benedick (2009, Chap.8 p.104.): "It was evident (...) that the protocol was in fact moving industry in directions that two years earlier had been considered impossible." Benedick refers to articles published in the *New York Times* and *Chemical and Engineering News* when he asserts that the agreement triggered a vast research effort.

[12] Parson narrates the various waves of research efforts to develop CFC substitutes, both before and after the signature of the Montreal Protocol. According to Parson, manufacturers would have stopped these R&D programs because they had determined that CFC substitutes would cost around 2 to 5 times more than CFCs, and it made no sense to continue developing these substitutes with little sign of regulations under way.

were readily available before the negotiations (Heal 2016; Sunstein 2007)[13]. This view is also often expressed in media outlets[14]. In this paper, I empirically investigate the role of Montreal in the development of CFC substitutes by quantitatively analyzing trends in patents and articles related to CFC substitutes.

1.3 Data

Empirical Indicators of Technological Change

Patents. The process of technological change is often described as a sequence of distinct activities: basic research, applied research, development, commercialization, and diffusion (Greenhalgh et al. 2010, figure 1.1). To strengthen the incentives to generate innovations, modern economies have adopted regimes of intellectual property rights where inventors are granted exclusive rights through patents. The publication of a patent, as a result, is a testimony to the successful process of applied research and development and can be considered as a proxy for technological change in general, and of innovation in particular. Patent data has been broadly used in empirical research in the past two decades (Hall et al. 2012; Henderson et al. 1998; Kay et al. 2014; Popp 2005; Williams 2013; Williams 2017). I follow this literature by using patent counts as a proxy for innovation. I download the full-text of all U.S. patent grants from 1976 to 2000 from the U.S.P.T.O. repository[15]. To construct a better proxy for innovation, I sort patent by application date. I use the texts contained in the

[13]Sunstein (2007), for example, claims that "an international agreement was largely in the interest of American manufacturers, which had already initiated a transition to safe CFC-alternatives". In a recent book examining the most urgent environmental issues of our time, Geoffrey Heal discusses the failure of the Kyoto Protocol in comparison to the success of Montreal: "However, there are big differences between ozone depletion and climate change. We have not yet seen the equivalent of DuPont's discovery of an alternative to CFCs, which would be the discovery by oil and coal companies of a greenhouse-gas-free energy source capable of meeting world energy demand at current energy costs." (Heal 2016, p68).

[14]Here is an excerpt from an article published in *The New York Times* on August 20, 2002: "The agreement's success occurred, in large part, because substitutes for the harmful chemicals were readily available (...)."

[15]This represents a total of 2,605,925 patents.

abstract and summary description of the invention. The cleaning procedure involves a series of standard steps such as replacing English contractions with their non-shortened forms or converting non-ASCII characters into their closest ASCII equivalents. More information is provided in Appendix 3.6. Patents also contain the names and addresses of inventors and assignees[16]. I also categorize patents by the type of organizations their assignee is affiliated with (e.g., business, education, or government). More details about how the meta-data is cleaned, matched and classified by type are provided in Appendix 3.6.

Articles. The phases of basic and applied research focus more specifically on the production and dissemination of knowledge. Through the publication of articles, researchers render their contribution public and allow other researchers and potential inventors to build upon it. A large literature was born out of Derek J. de Solla Price's contributions to a quantitative understanding of the growth of science (**Price1965**; **Price1986**; **Dasgupta.David1994**). More recently, scholars have analyzed the distribution of citations to understand differences between papers with low or high citations (**Thompson.Fox2005**; Iaria et al. 2015; Redner 2004; Wang et al. 2013). Part of the literature has also focused on the links between science and innovation by relating patents and scientific articles (Trajtenberg et al. 1997). Using Elsevier's web interface[17], I download the full-text of scholarly articles published between 1970 and 2000 in journals indexed by ScienceDirect[18]. First, I collect the ISSN number of each journal[19], and use the ScienceDirect API to obtain the DOIs of all the articles for each

[16]To associate patents to specific countries, I use the country of the assignee. When patents have no assignee but only inventors, I use the country of the inventor.

[17]http://dev.elsevier.com/

[18]I select journals in the following disciplines: chemistry, chemical engineering, engineering, environmental science, materials science, and physics and astronomy.

[19]I do this using Elsevier's website (`https://www.elsevier.com/solutions/sciencedirect/content/journal-title-lists`.

ISSN[20]. Then, I query the full text of articles for the DOIs returned[21]. After a series of cleaning procedures, I obtain a total number of articles of 1,811,301. I detect every document's language and drop non-English articles. Because the translation of English articles in other language is often contained in the full text, I drop any sentence containing less than 80% of tokens recognized by a standard English dictionary[22]. More details on the cleaning procedure are provided in Appendix 3.6. For data on affiliations and citation counts, I query the Scopus search API[23]. Additionally, I use the Global Research Identifier Database[24] (GRID) to classify authors' affiliations (e.g., education, company, etc...).

Molecule Groups

I primarily focus on a group of molecules that were known to be potential CFC substitutes. Since there is no preexisting categories or classification of such molecules, I construct a list using historical records. After Montreal, manufacturers from the US, Europe, and Japan received authorization from antitrust officials to organize cooperation, at least on the science for which patenting was not possible. They launched two working groups to study the feasibility of various alternatives. The PAFT (Program for Alternative Fluorocarbon Toxicity Testing), created in January 1988, worked on assessing the toxicity of five possible alternatives. The AFEAS (Alternative Fluorocarbon Environmental Acceptability Study), created in December 1988, investigated the atmospheric dynamics of twelve potential CFC substitutes. I use these twelve molecules to form a first group. I also include in this group two

[20] A DOI, or Digital Object Identifier, is a sequence of digits and letters that uniquely identifies an academic article.

[21] Full text data was successfully downloaded for 1,843,684 articles, out of a total of 2,307,345 DOIs initially returned by the API. This implies that Elsevier listed 463,661 DOIs for which the full text was not available. This might be due, for example, to entire journals dropping out of Elsevier Science Direct's collection.

[22] I use SpaCy's English dictionary in Python.

[23] Because of quota limitations, I queried meta-data only for articles mentioning only CFC substitutes, Annex A or B compounds.

[24] `https://www.grid.ac/`

other possible CFC substitutes mentioned in Benedick (2009) and Parson (2003)[25]. Table A2 in Appendix 3.6 shows the name and additional information about these molecules.

I search through every patent and article to identify which mention any of these molecules. Being able to search the full text of the documents is an advantage here since relying on abstracts only could lead to many false negatives. Chemical compounds, however, are often given several names; for example, HCFC-22 has 39 other possible names such as chlorodifluoromethane or algeon 22. To capture all the occurrences of a mention of a molecule, I develop an automatic script to collect all possible names for a given molecule through SciFinder, a database of chemical information maintained by the American Chemical Society. I then search through all patents and articles to identify which documents mention any of these molecule names. When a document contains the name of only one of the molecules, the document is assigned to that molecule. When it mentions several molecules, it is assigned to each of these molecules[26]. I develop alternative rules as robustness checks. I proceed similarly to identify the patents and articles that mention any of the 171 Hazardous Air Pollutants (HAPs). I explain in the next section how these molecules are useful for my methodology[27].

To illustrate the kind of patents present in the data, Table 1.1 lists the ten most common patent codes for patents mentioning CFC substitutes. Most codes belong to the C class ("Chemistry, Metallurgy"). The subclasses "C07" and "C08" refer in particular to the purification, separation or stabilization of organic compounds possibly containing carbon and halogens with or without hydrogen[28].

[25] HFC-245fa and HFC-365mfc are mentioned as possible substitutes in foams.

[26] This is what I refer to as the *weak* rule.

[27] The full list of HAP molecules that I consider is available in the supplemental online material.

[28] For example, C07C 19/00: Acyclic saturated compounds containing halogen atoms.

Topic Proportions

I use topic modeling, a machine learning method for text analysis (**Roberts.etal2014b**; Blei 2012; Blei et al. 2006, 2009; Roberts et al. 2016), to generate covariates that describe the semantics surrounding molecules. These covariates help describe and measure molecules' chemical and industrial characteristics. The procedure outputs document-level *topic proportions*, that is a variable from 0 to 1 indicating to what extend topic i is present in a particular document. I then aggregate topic proportions at the molecule level by calculating unweighted and weighted means with weights proportional to the number of times an article mentions a molecule. Figure 1.1 summarizes these various steps with a simple example of three documents, two molecules, and two topics. Appendix 3.6 provides a more detailed description of the procedure and the obtained topics.

1.4 Methodology and Results

A Sharp Post-1987 Increase

A simple approach to study patterns in patents and articles is to observe the yearly count of documents about CFC substitutes and test whether there is a change of patterns before and after the date of the signature of the agreement. Figure 1.2 plots the yearly number of articles or patents mentioning the names of any of the 14 CFC substitutes[29]. We note a clear increase after 1987, the year Montreal was signed. The hypothesis is that the signature of Montreal acted as a strong signal to the business community that prices were going to change and modified expectations regarding where future profits lay, i.e., in CFC substitutes. We shall add that the response to an international agreement should be greater if many countries participate in that agreement(Dekker et al. 2012). A global market means more profit-making opportunities for firms about to incur the sunk costs of research and development.

[29]Figure A3 in Appendix 3.6 displays similar trends for each of the 14 molecules.

For researchers publishing in peer-reviewed journals, the Montreal Protocol likely acted as a strong signal that a technological transition was underway inducing researchers to redirect their work towards CFC substitutes. Additionally, the choice of which scientific research to conduct can also be heavily influenced by organizations funding research, such as the National Science Foundation. Likely, research grants were directed on ozone depletion and alternatives to CFCs. These mechanisms can help explain why we observe a strong increase in patents and articles on CFC substitutes after 1987.

Innovation as a Driver of Montreal and Anticipation

An interesting question is whether R&D activities before 1987 eventually led to the success of the negotiations at Montreal. On Figure 1.2, the trend in patenting and publishing before 1987 looks not just astonishingly flat but also very small in terms of actual number of patents and articles published each year. This is indicative that, in fact, little was going on before Montreal on the science and innovation on CFC substitutes. The ozone crisis literature often mentions the existence of domestic regulations before 1987 as potential pre-Montreal drivers of innovation. For example, in August 1977, the U.S. Congress amended the Clean Air Act with the Stratospheric Ozone Protection amendment writing into law a CFC ban on aerosols by 1978[30]. In fact, even before any domestic regulation, some manufacturers unilaterally decided to remove CFCs from their spray products because they worried about their public image. Hence, consumer pressure possible acted as an incentive for firms to innovate. However, these pre-Montreal domestic regulations and unilateral actions on behalf of manufacturers only targeted aerosols, one very specific industrial application of CFCs for which substitutes[31] could easily and cheaply be implemented[32]. These product changes unlikely required a significant research effort. The low levels in patent and article count

[30]Similarly, in 1978, Canada, Switzerland and Scandinavian countries all banned CFC aerosols. On continental Europe, Germany called for a European Community-wide ban without success.

[31]Physical substitutes included roll-on devices; chemical substitutes included alkanes.

[32]In 1980, the EPA proposed to freeze other uses beyond aerosols but U.S. industry blocked the initiative.

between 1970 and 1987 on Figure 1.2 indicates that neither consumer pressure nor aerosol regulations seemed to have stimulated science and innovation on the 14 CFC substitutes I consider[33].

The flat trend in patenting and publishing before 1987 on Figure 1.2, additionally, indicates little anticipation of the negotiations' success. This is also supportive of the negotiations being little influenced by the research output on CFC substitutes. Indeed, if R&D output were key drivers to the negotiations' success, firms should have been able to anticipate the negotiations' outcome. Firms have strong incentives to be forward-looking because anticipating can confer a first mover advantage. By undertaking early-on research activities, they can develop cleaner technologies before competitors and build a strategic advantage when regulations are passed[34]. As a result, if the signature of Montreal had been anticipated, we would observe a gradual increase in patent and article counts starting before or at least close to 1987[35]. Instead, it seems firms believed the likelihood of regulations to be low and therefore had little incentive to invest in R&D.

This is, in fact, consistent with Benedick's accounts of the events (Benedick 2009): when the issue took prominence in the media and regulators' minds in the late 1970s, firms initiated some R&D projects regarding CFC substitutes. However, those projects were canceled by the early 1980s when the probability of regulation rapidly converged to zero. At that time, uncertainties in the science of atmospheric ozone seemed irreducible, and the year 1981 saw the election of a strongly anti-regulatory American administration. In Europe, many

[33]These 14 CFC substitutes were targeting foams, refrigeration and solvent applications of CFC.

[34]Firms with such competitive advantage could even decide to lobby in favor of environmental regulations for that reason (Puller 2006).

[35]It is difficult to pinpoint precisely optimal patenting timing. On the one hand, firms have an incentive to delay patenting right until production and commercialization begin because patents expire after ten years. This phenomenon is particularly salient for technologies with little risk of a competitor developing a comparable product. Patenting renders the output of a firm's R&D public knowledge, allowing potential competitors to effectively learn from it and come up with even better technologies. On the other hand, when competitors work on closely related projects, delaying patenting sharply increases the risk that competition patents first. This mechanism was likely salient in the case of CFC substitutes. Hence, overall, we should not expect CFC manufacturers to delay much of their patenting activity.

governments persisted in refusing to harm their domestic manufacturers with any regulation. Benedick emphasizes the complexity of the negotiations and the great uncertainty, until the last minute, of the negotiations' outcome. He further argues that some exceptional turns of events unlocked the situation. Unexpectedly, Reagan overruled his own administration and approved the agreement[36]. On the European side, the biggest opponent to the regulation of CFCs, the U.K., left the European Community Presidency, leaving Germany, Denmark, and Belgium, firm proponents, as the head negotiators. This account of the negotiations' success does indeed indicate that the agreement largely occurred independently from the state of R&D activities on CFC substitutes.

Consequently, it looks unlikely that science and innovation on CFC substitutes were strong drivers of the diplomatic efforts to regulate CFCs in Montreal. At this stage, I can not rule out that firms might have kept their CFC substitutes secret and discretely lobbied for the success of the agreement. I will investigate this possibility in Section 1.6.

First Differences

To quantitatively investigate the temporal patterns and detect a change happening in 1987 onwards, I implement the following econometric specifications: a first difference specification with a mean shift (Equation 1.1) and a first difference specification with a trend-break (Equation 1.2). $LogCount_{m,t}$ is the log number of documents in year t about molecule m; $\lambda_{post1987}$ is a dummy variable that equals one when $t > 1987$; λ_m are molecule fixed effects; $Years$ is a continuous variable indicating the number of years relative to 1987. Here, I suggest to use counts in log, instead of level, as the outcome variable since it will provide a better linear fit over time. Indeed standard models suggest we can think of scientific production as exponentially growing over time. The sample here consists of 14 different

[36]The U.S. President had a skin cancer removed twice in the past, and Benedick hints that Reagan's life experiences weighed heavily on his decision.

CFC substitutes of which I track the number of patents and articles throughout the years.

$$LogCount_{mt} = \alpha + \beta_0 * \lambda_{post1987} + \lambda_m + \epsilon_{mt} \tag{1.1}$$

$$LogCount_{mt} = \alpha + \beta_1 * Years * \lambda_{post1987} + \beta_2 * Years + \lambda_m + \epsilon_{mt} \tag{1.2}$$

The main hypothesis is that β_0 and β_1 are both positive for CFC substitutes, implying a significant increase in research and patenting activities relating to CFC substitutes after 1987 once Montreal passed. Table 1.2 displays the regression tables for the simple first time differences. Model 1 confirms that there is a significant and positive mean shift after 1987 in the number of patents and articles mentioning CFC substitutes. The coefficients corresponds to about 630% more patents and 190% more articles on CFC substitutes after 1987 (compared to before). Model 2 shows that the change can also be modeled as a trend break. The coefficient for "Years" indicates that there is a small positive underlying trend for both patents and articles. Figure A2 in Appendix illustrates that patent codes that the most frequent before 1987 tend to be the most frequent after 1987 as well. At the same time, some codes with low frequency before 1987 become important after 1987 (e.g., C08G, C10M, C23G or C11D). Figure A4 in Appendix illustrates that the increase in patenting activity applies to all countries; we note a particularly strong increase for Japan and the UK.

Because this is only a simple temporal difference, such an increase could also be due to other underlying trends not specific to ozone negotiations. For example, it might be possible that some other reforms or the economic context fostered more academic and industrial research in the 1990s. Hence, we need to find a group of molecules that could serve as a control group; the challenge consists in finding molecules that are very similar to the treated molecules, while, at the same time, remaining different enough to ensure that they are not affected by the treatment. Specifically, a good control group should contain molecules which undergo similar influences as CFC substitutes apart from the one of the Montreal Protocol. One way of choosing such molecules is such that they present similar pretreatment trend in the outcome variable $LogCount$ but also such that they are as close as possible to the treated molecules chemically, physically and regarding industrial applications. Such molecules can potentially be found in the pool of HAPs.

HAPs as a Comparison Group

HAPs have no connection to ozone but they are often related to industrial activities. They became monitored under the Clean Air Act due to human health concerns including cancer, asthma, birth defects, reproductive effects, and neurodevelopmental effects, as well as adverse ecological impacts. Examples include benzene, chromium or formaldehyde[37]. Figure 1.3 illustrates why HAPs are a good choice as control molecules: overall patents about CFC substitutes and HAPs fall into similar top-level codes. Additionally, Figure A5 shows that they also display similar second-level patent codes. Table A3 in Appendix 3.6 displays summary statistics about countries and affiliations of patent assignees and authors of articles[38]. The two groups have similar profiles: more than 96% of patents are granted to for-profit organizations. The rest is shared among organizations coming from the educational and governmental sector. Furthermore, the majority of patents are granted to assignee domiciliated in the United States. European assignees tend to represent around 20 to 30% of patents; Japanese around 10 to 20%.

On Figure 1.4, I plot the yearly mean counts of documents mentioning CFC substitutes and HAPs to check similarity in the pre-trends. When using the whole sample of HAPS (that is 171 HAPs molecules), pre-trends look similar. However, a close observation reveals that, in patents, pre-trends for CFC substitutes are slightly up, while the one for HAPs goes slightly down. In articles, HAPs have a clear upward trend before 1987 while CFC substitutes seem somewhat flatter. Similarity in pre-trends can be improved by selecting a subset of HAPs with pre-trend closest, in terms of log count, to the average CFC substitutes.

[37] The full list of the molecules included in the different treatment groups is displayed in the supporting online material.

[38] Data collection for HAPs in articles is still undergoing due to quota limitation on the Elsevier API.

Specifically, I construct the control group such that it contains the 42 HAPs whose pre-trend is closest to the average trend of CFC substitutes[39].

Difference-in-Differences

I estimate the DiD model with a mean shift specification (Equation 1.3) and a trend-break specification (Equation 1.4). $LogCount_{m,g,t}$ is the log number of documents with molecule m belonging to molecule group g, in year t; $Post_t$ equals one when $t > 1987$; D_m equals one if the molecule belongs to the treated group; λ_m are molecule fixed effects; λ_t are year fixed effects; $\boldsymbol{X}_{mt}$ is a vector of covariates; Y is a continuous variable indicating the number of years relative to 1987. β_0 identifies the DiD estimate.

$$LogCount_{mt} = \alpha + \beta_0 \cdot D_m \cdot Post_t + \lambda_t + \lambda_m + \boldsymbol{\gamma_t} \cdot \boldsymbol{X}_{mt} + \epsilon_{mt} \tag{1.3}$$

$$LogCount_{mt} = \alpha + \beta_1 \cdot Y \cdot Post_t \cdot D_m + \beta_2 \cdot Y \cdot Post_t + \beta_3 \cdot Y + \lambda_t + \lambda_m + \boldsymbol{\gamma_t} \cdot \boldsymbol{X}_{mt} + \epsilon_{mt} \tag{1.4}$$

The primary hypothesis is that β_0 and β_1 are positive. Significant coefficients would imply that the research and development activities underwent important changes after 1987 relative to the counterfactual. If there is no significance, this might suggest that the research effort was redirected towards CFC substitutes already before the signature of the treaty.

Table 1.3 displays the DiD results. Model 1 corresponds to the main differences-in-differences specification. It includes year and molecule fixed effects. The binary variable "Post 1987 x Substitutes" equals 1 for observations belonging to the group CFC substitutes and after 1987. For patents, the coefficient is smaller than the coefficient in the simple difference, but remains significant and large, corresponding to more than a 500% increase. This estimate corresponds to an additional 28 documents per year for the average substitute. Since there are 14 CFC substitutes in my sample, this implies 390 additional patents a year for CFC substitutes in aggregate. For articles, the coefficient is smaller than the

[39] I construct the control group such that it is three times larger than the treated group. There are 14 molecules in the treated group, hence I use 42 units in the control group (3×14).

coefficient in the simple difference, but remains significant and large, corresponding to more than a 95% increase. This corresponds to an additional three documents a year for the average substitute; hence, aggregating the 14 CFC substitutes, this corresponds to about 47 additional articles per year. Model 2 presents a trend-break specification. It shows that the log number of patents mentioning CFC substitutes increases with the years after 1987 by 0.22 more than the control group. Similarly, the log number of articles mentioning CFC substitutes increases with the years after 1987 by 0.10 more than the control group.

Figure 1.5 display the DiD coefficients plots. We note that, in patents, the treatment effect is small, yet statistically significant, as early as 1988. For articles, the treatment effect is first statistically significant in 1990. Two mechanisms can account for a delay between the moment firms decide to redirect their R&D efforts towards CFC substitutes and the granting of a patent. First is the time required to obtain any technology worth patentable, which can broadly vary. Second, to be granted a patent, firms must submit an application which is then reviewed by patent examiners. The average delay between application and granting for patents on CFC substitutes is 22 months (with a standard deviation of 12 months). It is very similar for patents on HAPs[40,41].

Accounting for a two-year delay on average indicates that the increase in patenting on CFC substitutes happened soon after the signature Montreal. It is difficult to assert how long it takes firms to develop new technologies in response to a change in incentives. We can expect such delay to vary from technology to technology even within the same technological sector. In the context of energy patenting, (Popp 2002) estimates that the mean lag occurs in 3.71 years and the median lag in 4.86 years. This implies that over one-half of the full effect of an energy price increase on patenting is experienced after just 5 years. These estimates are somewhat consistent with the shape of the yearly treatment effects obtained

[40] The average delay for patents on HAPs is about 23 months (with standard deviation of 12 months).

[41] Figure A6 in the appendix graphically shows the differences between application and granting date. Overall, plotting the number of patents based on granting dates simply shifts the entire curve two years forward. Importantly, the pretreatment periods look very similar.

here. One possibility is that firms developed technologies prior to 1987 keeping them secret. Once Montreal is agreed, it becomes worthwhile to patent as firms know they will eventually commercialize them. It is possible, therefore, that some patents granted soon after 1987 results from R&D effort incurred prior to Montreal. I will further investigate this question in section 1.6.

Table 1.4 compares the mean numbers of documents and topic proportions for patents and articles across CFC substitutes and HAPs. The two groups have very different average counts. Mean topic proportions are also statistically different across the two groups. For this reason, I run additional DiD specifications controlling for lags of log count and for topic proportions. Table 1.5 indicates that the treatment effects remain robust to those control variables. The magnitude of the treatment effects, however, is reduced.

1.5 Synthetic Control Method

SCM and DiD

DiD strategies are designed to estimate average effects over a population from which we sample a large enough number of units exposed and units non-exposed to treatment. Considering the overall population of potential CFC substitutes, I have sampled 14 of them; however, those 14 observations are not independent because several molecules are often mentioned in the same documents. Additionally, the reported standard errors in the DiD regressions reflect uncertainties about the aggregate data. This is problematic because the greatest uncertainty lies in the choice of the control group, and not in the aggregate quantities. In fact, here, the aggregate quantity can be thought of as observed: adding up the observed counts of the 14 CFC substitutes, and considering them as one single treated unit. Figure 1.6 plots the number of patents (in log) mentioning CFC substitutes. The thick line called "Substitutes (aggregated)" corresponds to the number of patents mentioning any of the 14 CFC substitutes. I implement the SCM on this aggregated substitute and I am interested in examining whether the aggregate count of these 14 substitutes has gone up compared to a control group. SCM was specifically developed to evaluate the effects of large aggregate interventions when the treatment affects an aggregate quantity (Abadie et al. 2003, 2010, 2015; Athey et al. 2016). Many interventions are in fact implemented at an aggregate level and have an impact on a small number of large entities, such as cities, school districts, or states. I enlarge the application of SCM to a new kind of aggregate entity: field of scientific and engineering inquiry.

The magnitude of the treatment effects estimated with the DiD strategy inherently relies on the choice of the control group. It is possible to improve those estimates by choosing the molecules that are included in the control group more precisely. Figure 1.7 in the appendix shows patent counts in log for each HAP and for the aggregated CFC substitutes. The graph illustrates the high heterogeneity within the group of HAPs, and in particular that many HAPs have log counts much higher than the aggregated CFC substitutes. Some of the HAPs might also be very different chemically, physically and from an industrial point of view. An improvement on using all HAPs in the control group is therefore to use only the HAPs whose yearly number of patents and articles are driven by structural processes most similar to those driving those of CFC substitutes. The selection of comparison units is crucial in such study: if too different from the treated unit, any deviation in the outcome after the treatment can be attributed to initial differences and the resulting estimate would be biased. The SCM offers a data-driven way to construct comparison units using only the HAPs most similar to CFC substitutes. Figure 1.8 illustrates why topic proportions are useful in this case. We see that some HAPs have values of topic proportions that stand out as outliers, indicating that those HAPs present a semantic context that is likely very different from the one of CFC substitutes. Using topic proportions together with the SCM ensures that such HAPs are not used in constructing a synthetic control.

The key idea of SCM consists in using a weighted average of a set of control units with the weights chosen so that the weighted average is similar to the treated unit regarding covariates and outcome in the pretreatment periods. For example, suppose we had 3 HAPs as control units with weights μ_a for asbestos, μ_b for benzene, and μ_c for catechol. Then the weights are chosen such that $\mu_a \times Y_{at} + \mu_b \times Y_{bt} + \mu_c \times Y_{ct}$ is close to Y_{St} (where S stands for substitutes) for periods t before the treatment takes place. Here, Y is the log count of articles mentioning the molecule, but additional covariates can be used. The advantages of SCM relies on the opportunity to create a synthetic unit that shares as much as possible the characteristics of the treated unit. In my case, I would hope to construct a synthetic unit that not only reproduces the path of counts in pretreatment periods, but that also resembles the treated molecules regarding chemical, physical and possibly industrial characteristics. To this aim, I attempt to proxy such characteristics with topic proportions derived from topic modeling of the documents' text. I explain this further in details in the next section.

Implementing SCM

I implement the SCM using log count as the main outcome variable considering the 14 CFC substitutes as one treated molecule. The outcome variable is therefore the log number of patents or articles that mention any of the 14 molecules. The synthetic control is constructed by fitting the values of log counts in the pretreatment periods and the topic proportions. I run specifications using the weighted means and the non-weighted means of topic proportions. It is critical to ensure that the synthetic control closely matches the treated unit in the pretreatment periods. If that was not the case, the synthetic control unlikely provides a good proxy of a counterfactual since it is not even a good proxy of the treated unit before treatment. Following Abadie et al. (2010), I examine the Root Mean Square Prediction Error for periods before treatment (pre-RMSPE)[42] to verify whether the discrepancies between the synthetic control and the treated unit are large and thus whether the SCM is appropriately

[42]The pre-RMSPE measures lack of fit between the path of the outcome variable for any particular unit and its synthetic counterpart: the pre-RMSPE of unit 1 is defined as $(\frac{1}{T_0}\sum_{t=1}^{T_0}(Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}))^{1/2}$ where T_0 is the number of pretreatment periods. A post-RMSPE can be similarly defined for periods going from $T_0 + 1$ to the end of time-series available.

implemented.

Finally, I use the 171 HAPs as units in the donor pool. However, as explained by Abadie et al. (2015), reducing the size of the donor pool can limit the risk of over-fitting as well as the risk of interpolation biases. Following their advice, I use a smaller donor pool containing only the HAPs that are close to the treated unit in the space of covariates and outcome. I choose the twenty HAPs with lowest pre-RMPSE, that is the twenty HAPs that are closest to the treated unit in terms of topic proportions and count. In what follows, I call this group of HAPs the "smaller" donor pool. I refer to the "whole sample" of HAPs when the donor pool includes the 171 HAPs. In all the SCM specifications, the treatment year is the first year in which the treatment becomes active: this is defined as 1988 since Montreal was agreed in 1987. To be conservative, I use data from 1970 until 1985 only to fit the synthetic control.

For inference, I follow the method suggested by Abadie et al. (2010) and Abadie et al. (2015). The exercise consists in applying the SCM procedure to every potential control in my sample. This allows me to assess whether the effect estimated for the unit treated is large relative to the effect estimated for a molecule chosen at random. This is akin to implementing placebo tests wherein each unit in the control group is assumed to have received the treatment at the year 1987. A synthetic control is then constructed for each placebo, and we observe what would have been the hypothetical treatment effect for this "falsely" treated unit. This creates a distribution of placebo effects, and we can evaluate the effect for the "true" treated unit vis-a-vis to where it falls in this distribution. A p-value is calculated as the fraction of placebo effects that are greater than or equal to the effect estimated for the "true" treated unit.

As suggested by Abadie et al. (2010), it is useful to compute the ratios of post-RMSPE over pre-RMSPE and examine where in the distribution of those ratios, the treated unit lies. For example, if the treated unit is second largest ratio among a donor pool of 50 units, then the p-value can be computed as $\frac{2}{50} = 0.04$, and the treatment effect would be significant at the 5% level[43]. The p-value can be interpreted as the probability of obtaining an estimate at least as large as the one obtained for the "true" treated unit. Hence the inference is mostly limited to assessing whether the treated effect is large compared to the distribution of the placebos. To illustrate, how p-values are calculated, Figure 1.9 displays the distribution of post-RMPSE over pre-RMPSE for the case of log count, weighted means of topic proportions and the whole sample of HAPs, for the corpus of patents. The figure shows that the ratio for CFC substitutes is greater than all of the 168 other units. Hence the p-value, in this case, is 1/168.

Finally, when choosing weights for the donor units to create the synthetic control, the SCM algorithm imposes that the weights sum to 1 and that they be nonnegative. These constraints avoid any risk of extrapolation. However, when the treated unit presents values for covariates that are either the smallest or the largest in the distribution of the donors, it becomes difficult to approximate it. To verify that the donor pool remains adequate, Table A4 presents summary statistics for CFC substitutes and the small pool of HAPs in the case of counts derived from the weak rule. It is reassuring to see that the range of values displayed by the HAPs always contains the value for CFC substitutes. Hence, here, the constraints that weights must sum to 1 and be non-negative does not seem to be an issue.

SCM Results

Before examining results, I want to illustrate the benefits of the SCM. Table A6 compares the mean value over the years 1970 to 1985 of log count and topic proportions for CFC substitutes, the observed treated unit ("real S" in the table), for the comparison unit constructed through the SCM ("Synthetic S") and for the average of HAPs[44]. We see that

[43] The treatment effect's p-value for the treated unit is therefore defined as: $p_1 = \frac{\sum_{j=2}^{J+1} 1\{ratio_1 \geq ratio_j\}}{J}$, where $ratio_j = \frac{post-RMPSE_j}{pre-RMSPE_j}$ and subscript 1 refers to the treated unit.

[44] Specifically, the HAPs used in calculating the average are only those from the small pool. The synthetic control, here, was constructed based on similarity with the variables "Log count" and the weighted means of the five topic proportions.

the synthetic control matches the "real" CFC substitutes group better than the average of HAPs in terms of log count. This is the core idea motivating the use of the SCM[45]. Table A5 illustrates that topic proportions contribute around 15% in constructing the synthetic control[46].

Table 1.6a summarizes the performance of the main SCM implementations for CFC substitutes in the corpus of patents. I ranked the table according to the magnitude of the pre-RMPSE with smaller pre-RMPSE at the top of the table. The lower the pre-RMPSE, the better the fit between the synthetic control and the treated unit over pretreatment years, and therefore the more credible it is that the synthetic control appropriately proxies the counterfactual. Furthermore, recall that procedures using the small pool are more trustworthy because they limit the risk of interpolation biases and overfitting. Hence the preferred specifications here uses the small pool and the weak rule and weighted means of topic proportions. The p-values smaller than 0.01 indicate significance at the 99% level. Table 1.6a also reports the year in which the treatment begins to be significant at the 10% level. This is determined by calculating p-values for each year separately. We see here that the treatment effect becomes significant in most cases only starting in 1990 or 1992. The ATE for the preferred specification equals 0.89; this corresponds to a 144% increase in patents compared to the synthetic control; this gives a treatment effect close to 117 patents per year.

Similarly, Table 1.6b provides performance summary for the main SCM procedures for CFC substitutes in the corpus of articles. Here, the preferred procedure to report the ATE uses the small pool of HAPs and weighted means of topic proportions. The ATE for this preferred specification equals 1.06 and is significant at the 99% level. This estimate translates to a 189% increase, and corresponds to about 43 additional articles per year.

Figure 1.10 graphically displays the results of the SCM for CFC substitutes. The graphs

[45] The topic proportions are very similar, but this could be expected since the pool of HAPs used is the small one, and the means of topic proportions within that pool are very concentrated.

[46] In the Stata *synth* package, these weights are determined according to the amount of predictive power that each variable has over the outcome. Hence, in the case of patent counts with weighted means of topic proportions, the outcome variable, log count, is the variable assigned greatest weights.

correspond to SCM implementation for the preferred specification, that is when the SCM is implemented with log counts, using the small pool of HAPs and weighted means of topic proportions. The graphs on the left-hand side represent the raw effect, that is the observed time series of the treated group along with the time series of the constructed control. On the right-hand sides are shown the placebo tests, the non-parametric tests to evaluate the significance of the results; black lines show the effect on the treated group relative to the control group, while each gray line is a placebo test performed on a unit drawn from the donor pool.

The figure illustrates what we concluded from Table 1.6b and 1.6a: the treatment effect on CFC substitutes appears significant for both patents and articles. We note that the black line rises above most other lines mostly as from 1990. This indicates that, similarly as in the DiD, the treatment effect is statistically significant only after 1990.

Verifying SCM Assumptions

Anticipation. An important assumption supporting the SCM is that the intervention does not affect the outcome before the implementation period. In reality, anticipation effects often violated this assumption; part of the treatment effect would become embedded in the control, and the SCM would lead to understating the treatment effect. A workaround consists in redefining the treatment year as the first period in which the outcome may react to the intervention. I have already discussed that anticipation seems unlikely. However, I nonetheless replicate the SCM using 1985 as the beginning of the treatment since it was in March of that year that the Vienna Convention was adopted. The meeting in Vienna can be considered as the start of the ozone layer's diplomatic life. Figure 1.11 displays the SCM graphs for the preferred specification: it uses the small pool and weighted means of topic proportions for both patents and articles. Here, the earliest possible take-off would be in 1983 since I fit the synthetic control using data up to 1982. We observe that there does seem to be no takeoff before 1987 and results are very similar to fitting the synthetic control up to 1986.

Interferences A second assumption supporting the SCM requires that there be no interferences between units, meaning that HAP molecules should not be affected by the Montreal Protocol. This is unlikely to be the case since HAPs have been under the regulatory radar for very different reasons than ozone depletion. However possibly the redirection of research efforts towards CFC substitutes could crowd out financing towards the control molecules. This is also unlikely since HAPs are used in different types of industrial activities. However I still proceed to a careful examination of the firms patenting both on CFC substitutes and the top HAPs contributing to the synthetic control. Table 1.7a and 1.7b provide a description of the top 4 HAPs entering the synthetic control for patents and articles, respectively. We note that many of the industrial applications are not directly related to those of CFC substitutes which indicate a crowding out is unlikely. I investigate to what extend the assignees of patents on CFC substitutes and on those top 4 HAPs are similar. Unfortunately, assignee names in patent records are not standardized and the same firm can appear under different variations of the same name. I therefore use a fuzzy matching algorithm in order to match assignee names. I find that about 60% of patents mentioning CFC substitutes after 1987 are issued to assignees that never patented on any of the top 4 HAPs[47]. Examples of such assignees are firms like 3M, Allied Chemical, BASF, Dow Chemical and Procter & Gamble.

Robustness Checks

Molecule Frequency Figure 1.12 illustrates that focusing on patents and articles that contain more than just one occurrence of molecule would change little of the analysis. Indeed the trend of the average HAPs remain very similar; only the levels decrease as we increase the threshold of occurrence. For CFC substitutes, focusing only on patents with greater number of occurrences in fact seems to exacerbate the differential between the pre and post

[47] There are a total of 535 different assignees patenting on CFC substitutes after 1987, and 125 of those assignees about 25% also detain patents on one of the top 4 HAPs.

trends. Figure 1.13 shows results are robust to using patent counts weighted by molecule occurrences.

Counts in Level I replicate the SCM procedures using counts, in level and not in log, as the outcome variable. Table A7a and Table A7b display the results for patents and articles, respectively. Under the weak rule of assigning documents, I find an ATE that equals about 111 additional patents every year from 1988 to 2000, significant at the 99% level. This estimate is very close to the treated effect obtained using logged counts, which was about 100 patents per year. For articles, the ATE for the preferred specification equals about 44 additional articles every year from 1988 to 2000, significant at the 99% level. Like in the case of patents, this estimate is very close to the treated effect obtained using logged counts, which was about 40 articles per year.

Other Assignment Rules I consider a different rule for assigning document to molecules to test the robustness of my main results. Under the basic rule, which i call the *weak* rule, a document was assigned to group X if a molecule of group X is mentioned in the document, regardless of whether molecules from other groups are also mentioned. Now, under the new rule, which I call the *intermediate* rule, a document is assigned to group X if the molecule with the greater number of mentions is from group X. Figure A7 in the appendix shows the number of patents and articles every year for each molecule group according to the three assignment rules. We note that, as expected, the weak rule displays a greater number of documents, except for HAPs for which the weak and intermediate rules overlap almost completely. Table in the appendix A8 displays the performance results of the SCM procedures for patents and articles, respectively. We see results are very similar to the main specifications. The estimated treatment effects are somewhat larger than those with the weak rule. The pre-RMSPE values for patents however indicate that the synthetic control using the weak rule provided a better fit.

Other Robustness Checks I increase the number of topics generated by the LDA topic model from five to ten. I, therefore, use ten different topic proportions as covariates in the SCM procedure. Results are displayed in Table A9 in the appendix. I find similar treatment effects. Finally, since I implemented a DiD design using the particular subset of HAPs, I also implement the SCM using that subset as the donor pool. I find results that are comparable to the main specification. Details are reported in the supplemental online material. For patents, the treatment effect found approximates 0.9, while for articles it is lower than 0.80. We note that the values of pre-RMSPE are higher than the ones for similar procedures using the small pool. This implies that the procedure to select the subset based on similar slope excluded some molecules which ended up being useful contributions to the synthetic control.

1.6 Further Results

Influential Patents and Articles

In this section, I show that the most influential patents and articles were published after Montreal. Indeed, a possible alternative explanation is that despite most patents and articles being published after Montreal, the most influential ones happened before the signature of the treaty. Figure 1.14 indicates that, on the contrary, highly cited patents and articles concentrate after 1987[48]. I also implement an SCM using patent counts weighted by the number of citations each patent received and find strong treatment effects (see Figure 1.15). Similarly, Figure 1.13 shows results are robust to using patent counts weighted by patent citations. Table 1.8 displays the titles of the most cited articles mentioning CFC substitutes. Only articles with three molecule occurrences in the text were kept in the sample. We note that these articles, as expected, seem to focus on chemical and physical characteristics of CFC substitutes ("boiling", "evaporation", "pressure" etc...).

[48] Graphs 1.14a and 1.14c include patents and articles, respectively, that mention at least one occurrence of a molecule. To test the robustness of this findings, I plot similar graphs but for patents and articles that mention at least 3 occurrences in Figure 1.14b and 1.14d.

Secret CFC Substitutes?

Is it possible that firms initiated the transition to CFC substitutes before the Montreal Protocol, without patenting but instead keeping their technologies as trade secrets? Indeed, some firms announced at the end of the 1970s that they started R&D into CFC substitutes. Although the same firms soon after announced they terminated those R&D programs, it has been suggested that they might have developed key technologies that they kept secret. Figure 1.16 indicates that the post-Montreal burst of innovations on CFC substitutes is not driven by a few firms that would have been historically patenting on CFC substitutes since the 1970s. This finding cast the first doubt on the secret substitutes hypothesis. Specifically, Figure 1.16a shows that after Montreal there are many more firms with patents mentioning CFC substitutes and HAPs. It indicates the likely presence of new entrants in the post-1987 period. Figure 1.16b confirms this phenomenon by plotting the yearly number of assignees that are "new", meaning it is the first time they appear in the data with a patent mentioning CFC substitutes and HAPs. The figure shows that, after 1987, many firms with no prior experience on CFC substitutes begin patenting.

Additionally, if secret CFC substitutes existed, we would expect a one-time increase in patent counts in the immediate aftermaths of Montreal. Figure 1.17 plots the number of patents mentioning CFC substitutes by month in the two years that followed Montreal. We see in the first graph that there is no patenting peak. Furthermore, if the extent of R&D efforts provided before Montreal was the key driver to the post-Montreal increase in patenting, we should observe major differences in the patenting trends of old and new entrants. On the second graph, I present trends for assignees that never obtained any patent mentioning CFC substitutes before 1987 and those who did. Although a gap seems to build up over time, trends look mostly similar.

Zooming in on Key Manufacturers

Figure 1.18 illustrates the possible key role of a few manufacturers: the scatter plot shows, for each firm in the sample, the number of patents between 1975 and 1986 on the x-axis and the number of patents in the two years that followed Montreal on the y-axis. We see that a positive trend is mostly driven by three firms: Du Pont, Allied, and Dow. Excluding those, there are no clear correlations between patenting before 1987 and patenting in the immediate aftermaths of Montreal. This plot, however, motivates a more detailed investigation in the behavior of Du Pont and Dow. Figure 1.19a shows that most patents granted to Du Pont and Allied were applied for after 1989. Figure 1.19b shows that there is no sudden peak patenting right after Montreal. Instead, we observe a gradual ramping up of patenting activity. Figure 1.19c illustrates that the patents granted to Du Pont and Allied which received the greatest number of citations mostly originate from 1989 to 1991. Figure 1.19d indicates, however, that, in the weeks that followed Montreal, both Du Pont and Allied applied for patents that would go on receiving a high number of citations. This seems to indicate that Du Pont and Dow likely had a first mover advantage on some technologies. However, the magnitude of the ramping up in patenting activity that follows from 1990 onwards allows concluding that most of the innovative activity started after Montreal.

Annex A and Annex B Compounds

In this section, I investigate the effect of Montreal on patents and articles mentioning CFCs, that is the molecules which were being phased out of industrial activities. These molecules are referred to as Annex A compounds because they are listed in the Annex A of the legal text. These molecules include five chlorofluorocarbons and three halons. For chlorofluorocarbons, the agreement imposed a freeze by 1989 and a 50% decrease by 1998 relative to 1986; for halons, only a freeze by 1992 was decided. In 1990, during the London revisions, twelve additional compounds became regulated. They are listed in the Annex B of the agreement and consist of 10 other CFCs plus carbon tetrachloride and methyl chloroform.

The negotiated reduction targets for each compound is shown in the Appendix. In what follows, I refer to these two groups of molecules as Annex A and Annex B.

It is difficult to make strong hypotheses about the effect of Montreal for Annex A and Annex B compounds. On one hand, Montreal can be thought of an inventive to no longer pursue any research or innovation that would make use of these molecules in new industrial contexts. But the agreement might also have spurred research efforts to help reduce the ongoing effect of such molecules on the environment as well as innovations to help recycle such components or use them more efficiently. This second effect is particularly likely as the phase-out of such molecules was scheduled to be progressive. As a result, firms were given some time to adapt and could continue using CFCs in their production.

The graphs in Figure A8 plot the yearly number of articles or patents mentioning the names of given molecules included in Annex A and B. We note that most trends are flat, except maybe for Annex A in articles which seem to increase and then decrease. Table A10 presents results from first differences specifications. Results indicate statistically significant mean shifts between before and after 1987, except for Annex B in patents; however these are small in magnitude. In figure A11, the DiD specifications indicate that a positive and statistically significant treatment effect for Annex A in patents and a negative one for Annex B in articles. The magnitudes however are small. For Annex A in patents, the coefficient corresponds to a 18% increase in the number of patents mentioning Annex A compounds. For Annex B in articles, the estimate corresponds to a 28% decrease in the number of articles mentioning Annex B compounds.

Table A12 displays the summary performance of the SCM implementations for Annex A and B in patents and articles. Almost none of the implementations find a significant treatment effect, except for Annex B in articles where a negative treatment effect with 10% significant is found when the whole sample of HAPs is used. These results indicate that Montreal did not trigger a large decrease nor a large increase in the number of patents and articles mentioning Annex A and B compounds. Figure A9 and A10 illustrate these results by displaying the graphs generated by the SCM procedures using the small pool, and unweighted or weighted topic proportions (which ever gave lowest pre-RMPSE). The graphs show that indeed the estimated treatment effect estimated falls well within the distribution of placebo effects, at least for Annex A compounds. For Annex B compounds, the treatment effect tends to be as one of the lowest curves among all the placebos. We note that, in the case of articles, the synthetic control fails to provide a good fit, and so results cannot be trusted.

1.7 Conclusion

Tackling environmental problems often relies on developing and diffusing new technologies. It is, therefore, important to better understand the drivers of technological change. In this paper, I document that the Montreal Protocol, and its following amendments, led to the development of CFCs substitutes. This empirical evidence goes against the often-heard narrative that alternatives technologies were readily available before the treaty. In fact, sociologist Reiner Grundmann dubbed this idea "the most pervasive and most widespread myth surrounding the Montreal Protocol" (Grundmann 1998). He traced its origin to the fierce opposition between Americans and Europeans: the British and the French believed that environmental issues were a disguise for commercial interests, and that American manufacturers would use international regulations to gain market shares thanks to their secret substitutes[49]. Instead, the treatment effect that I estimate in this paper tells a story where almost all of the science and innovation on CFC substitutes was triggered by the post-Montreal regime. The magnitude of the effect is even consistent with what has been described as a "burst of industrial creativity" (Meadows et al. 1992).

[49] An element that helps better understand this accusation is the Concorde controversy from 1974 (Benedick 2009, p. 33). When the French and the British had hoped to conquer the world with supersonic jets, Americans denied them the authorization to land the aircraft on U.S. soil, protesting that the pollution emitted by the plane's engine was a serious threat to the ozone layer. These claims were dismissed later on as it was shown that the atmospheric reactions would not occur at the Concorde flying altitudes. This incident certainly left an aftertaste of distrust for Europeans.

The signature of Montreal triggered a series of mechanisms that provided firms and researchers clear incentives to orient their R&D effort towards CFC substitutes. In particular, it had the immediate effect of modifying expectations about future prices and created a worldwide demand for substitutes. Hence, it incentivized profit-seeking firms to bring CFC substitutes to market. Researchers publishing in peer-reviewed journals also redirected their work towards CFC substitutes either incentivized by grants focusing on ozone depletion or due to a shift in their personal research priorities. The science of ozone at the time was also evolving. Particularly, in 1985, scientists detected a large depletion of ozone over Antarctica (called the ozone "hole") and causally attributed it to CFCs in March 1988. This discovery certainly increased the perceived benefits of phasing-out CFCs and contributed to the deepening and widening of the ozone regime in London in 1990 and Copenhagen in 1992[50]. In future work, I aim at investigating to what extent the strengthening evidence of the urgency to phase-out CFCs might have directly incentivized firms to develop on CFC substitutes. Firms as profit-seeking entities are unlikely to react strongly. In a world without the Montreal agreement, firms would be weakly incentivized to incur R&D costs without the guarantee of their competitors doing the same and without the guarantee of a worldwide market, even with a large ozone hole over Antarctica and strong consumer pressure. Nonetheless, I intend to tease out the possible effect of the ozone hole "discovery" by leveraging variation in the timing of regulation of different molecules. Specifically, two molecules (carbon tetrachloride and methyl chloroform) were recognized as strong ozone-depleting substances but were not included in the 1987 agreement. Instead, they became regulated in 1990. I intend to analyze trends in science and innovation for substitutes to carbon tetrachloride and methyl chloroform to infer whether the ozone hole "discovery" might have directly affected firms' behavior.

[50]By deepening, I mean that more ambitious reduction targets were agreed. Widening refers to adding new molecules to the list of regulated compounds.

Table 1.1: Ten most common patent codes for patents mentioning CFC substitutes

ICL	Count	Description
C07C	501	Acyclic or carbocyclic compounds
C08G	351	Compounds of unknown constitution
C08J	269	General processes of compounding
C09K	183	Materials for applications not otherwise provided for
A61K	156	Preparations for medical, dental, or toilet purposes
C10M	106	Lubricating compositions
F25B	90	Refrigeration machines, plants, or systems; heat pump systems
C08F	67	Macromolecular compounds obtained by reactions only involving carbon-to-carbon unsaturated bonds
C11D	64	Detergent compositions
C07D	63	Heterocyclic compounds

Note: The table displays the most frequent codes associated to patents mentioning CFC substitutes throughout the period 1976 to 2000. Most codes belong to the C class ("Chemistry, Metallurgy"). The subclasses "C07" and "C08" refer in particular to the preparation (e.g., purification, separation or stabilisation) of organic compounds, and as such they are associated to any patent related to compounds containing carbon and halogens with or without hydrogen (e.g., C07C 19/00: Acyclic saturated compounds containing halogen atoms). Subclass 'C08G' is used to classify any preparation that uses fermentation or enzyme-using processes. Only patents with at least 3 molecule occurrences are kept in the sample.

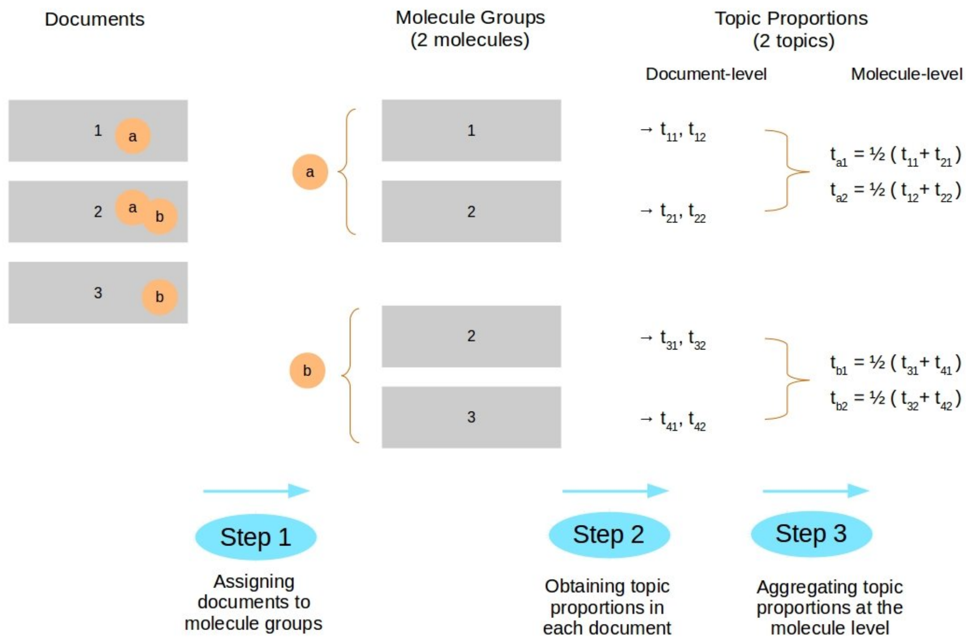


Figure 1.1: Schematic explanation of the methodology

Note: Suppose there are three documents: document 1 and 2 mention molecule 'a' while document 2 and 3 mention molecule 'b'. In step 1, I aggregate documents according to their molecule group. I follow a basic rule that assign any document with at least one mention of a molecule to that molecule's group. In step 2, I use topic modeling to obtain the proportions of topics in each document. t_i, j stands for the proportion of topic j in document i. Finally, in step 3, I create a topic proportion at the molecule level by averaging over all the documents that mention the molecule of interest.

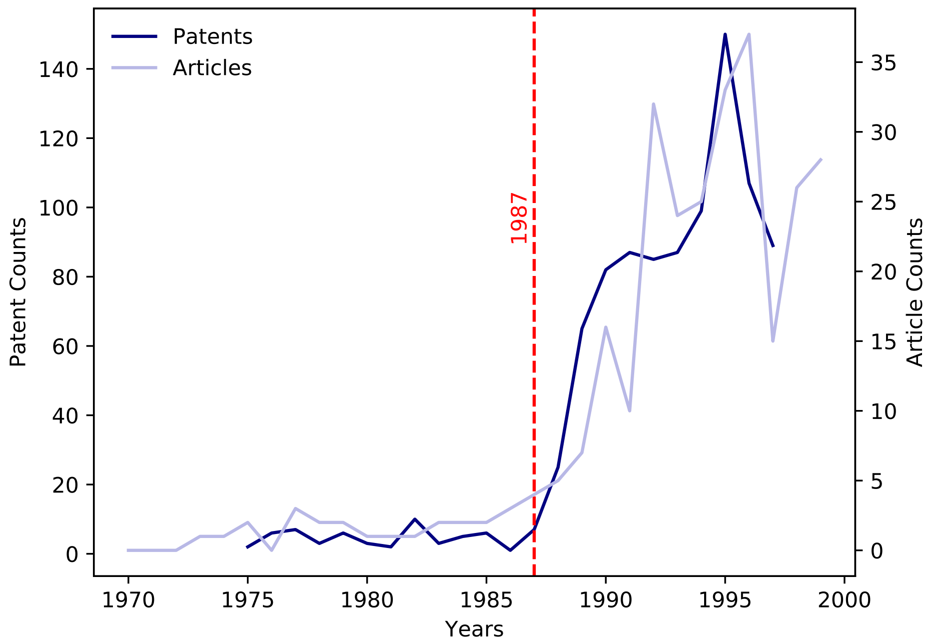


Figure 1.2: Counts of patents and articles on CFC substitutes

Note: The graph plot the yearly number of articles or patents mentioning the names of any of the 14 CFC substitutes. This is not the average count of the 14 different CFC substitutes but the total count of documents mentioning any one of the 14 CFC substitutes. We note a clear increase for both patents and articles after 1987, the year Montreal was signed. For patents, the graph shows any patent *granted* (as opposed to patent applications) between 1976 and 1999. The year on the x-axis, however, corresponds to the application date. There is on average a two-year delay between patent application and grant. For articles, the year on the x-axis corresponds to the year the article was published in the academic journal.

Table 1.2: First differences for CFC substitutes

(a) Patents

	(1)	(2)
Post 1987	1.840^{***}	1.268^{***}
	(0.077)	(0.165)
Post 1987 x Years		0.095^{***}
		(0.026)
Years		0.000
		(0.012)
Molecule FE	Yes	Yes
R-squared	0.789	0.809
Observations	322	322

Standard errors in parentheses
Dependent variable: Log count of patents
Years are relative to 1987.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Articles

	(1)	(2)
Post 1987	1.053^{***}	0.344^{***}
	(0.067)	(0.119)
Post 1987 x Years		0.083^{***}
		(0.016)
Years		0.011^{*}
		(0.006)
Molecule FE	Yes	Yes
R-squared	0.649	0.693
Observations	420	420

Standard errors in parentheses
Dependent variable: Log count of articles
Years are relative to 1987.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The tables present regression results for first difference specifications. Model 1 confirms that there is a significant and positive mean shift after 1987 in the number of patents and articles mentioning CFC substitutes. Model 2 indicates that the change can also be modeled as a trend break. The coefficient for 'Years' indicates that there is a small but statistically significant positive underlying trend for both articles and patents.

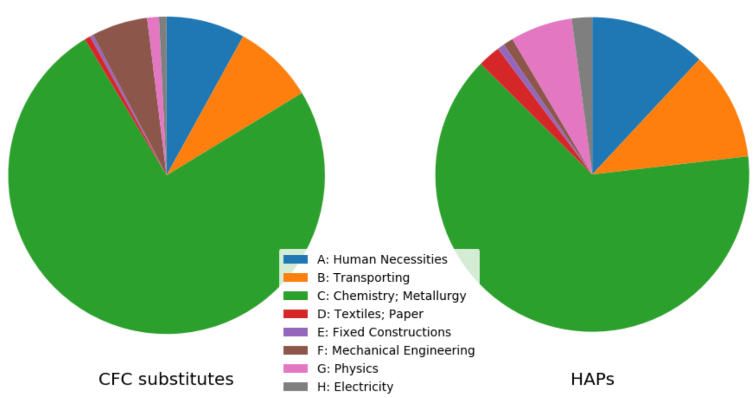
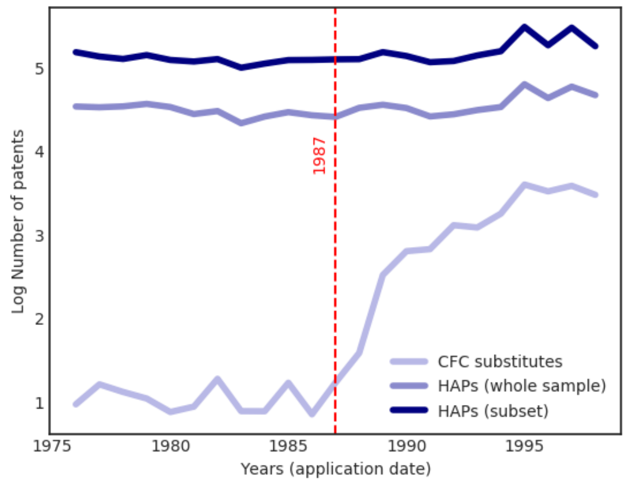
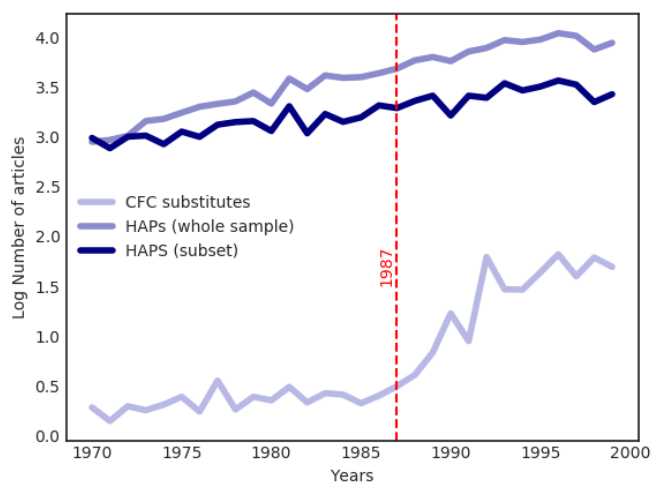


Figure 1.3: Top level patent codes for CFC substitutes and HAPs

Note: The figure shows that, overall, patents mentioning CFC substitutes and HAPs fall into similar top-level codes. HAPs are a group of 171 molecules that have no relationship to ozone and that are used for diverse industrial applications. The figure indicates the two groups of molecules present important similarities which motivates the use of HAPs as control molecules to estimate the causal effect of the post-Montreal regime. The patent codes are from the international patent classification.



(a) Patents



(b) Articles

Figure 1.4: Pre-trends in log counts of documents mentioning CFC substitutes and HAPs

Note: The graphs display the pre-trends for the treated group (CFC substitutes) and two possible control groups. The first uses the whole sample of HAPs (that is 171 molecules). In this case, pre-trends look somewhat similar. Pre-trends are, however, closer when using a smaller subset. Specifically, the second control group, shown as ”subset” on the graphs, uses a smaller number of HAPs: the 40 HAPs with pre-trends closest to the average CFC substitutes.

Table 1.3: Difference-in-differences for CFC substitutes

(a) Patents

	(1)	(2)
Post 1987 x Substitutes	1.858***	1.078***
	(0.072)	(0.169)
Post 1987 x Substitutes x Years		0.095***
		(0.026)
Substitutes x Years		0.018
		(0.012)
Years		-0.018***
		(0.004)
Post 1987		0.190***
		(0.036)
Year FE	Yes	No
Molecule FE	Yes	Yes
R-squared	0.974	0.967
Observations	1288	1288

Standard errors in parentheses
Dependent variable: Log count of patents
Years are relative to 1987.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

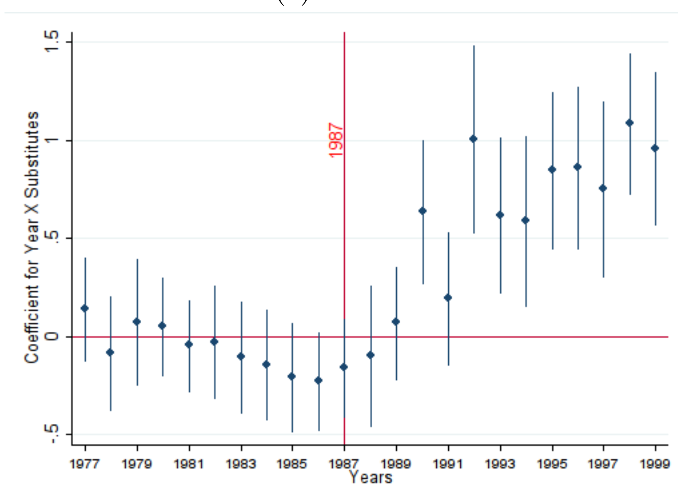
(b) Articles

	(1)	(2)
Post 1987 x Substitutes	0.727***	0.291**
	(0.068)	(0.126)
Post 1987 x Substitutes x Years		0.083***
		(0.016)
Post 1987		0.052
		(0.041)
Substitutes x Years		-0.007
		(0.006)
Years		0.018***
		(0.002)
Year FE	Yes	No
Molecule FE	Yes	Yes
R-squared	0.947	0.947
Observations	1680	1680

Standard errors in parentheses
Dependent variable: Log count of articles
Years are relative to 1987.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The tables present regression results for the difference-in-differences specifications. Model 1 corresponds to the main DiD specification. It includes year and molecule fixed effects. The binary variable 'Post 1987 x Substitutes' equals 1 for observations belonging to the group CFC substitutes and after 1987. For patents, the coefficient is smaller than the coefficient in the simple difference, but remains significant and large, corresponding to close to a 550% increase. For articles, the coefficient is smaller than the coefficient in the simple difference, but remains significant and large, corresponding to more than a 95% increase. Model 2 presents a trend-break specification. It shows that the log number of patents mentioning CFC substitutes increases with the years after 1987 by 0.22 more than the control group. Similarly, the log number of articles mentioning CFC substitutes increases with the years after 1987 by 0.10 more than the control group.

(a) Patents



(b) Articles

Figure 1.5: Difference-in-differences treatment effects by year

Note: The graphs display the DiD coefficients for each year. We note that, in patents, the treatment effect is statistically significant, yet small, as early as 1988. For articles, the treatment effect is first statistically significant in 1990.

Table 1.4: Balance table between CFC substitutes and HAPs

(a) Patents

	HAPs	CFC substitutes	Difference	T-stat
Number of patents	465.70	16.37	449.34***	(13.12)
Log number of patents	4.91	1.93	2.98***	(24.19)
Weighted mean proportion of topic 1	0.19	0.16	0.04***	(9.24)
Weighted mean proportion of topic 2	0.10	0.09	0.02***	(7.14)
Weighted mean proportion of topic 3	0.41	0.33	0.08***	(10.22)
Weighted mean proportion of topic 4	0.18	0.13	0.04***	(11.59)
Weighted mean proportion of topic 5	0.07	0.07	0.00	(1.67)

(b) Articles

	HAPs	CFC substitutes	Difference	T-stat
Number of articles	159.92	3.28	156.64***	(6.46)
Log number of articles	3.23	0.78	2.46***	(26.21)
Weighted mean proportion of topic 1	0.19	0.11	0.09***	(21.10)
Weighted mean proportion of topic 2	0.30	0.15	0.15***	(26.70)
Weighted mean proportion of topic 3	0.12	0.05	0.06***	(24.54)
Weighted mean proportion of topic 4	0.19	0.09	0.09***	(24.76)
Weighted mean proportion of topic 5	0.16	0.07	0.10***	(28.34)

Note: The table shows the mean of the outcome variable (in log and in level) and the topic proportions for patents and articles on CFC substitutes and HAPs. We see that the two groups have very different average counts. Mean topic proportions are also statistically different across the two groups.

Table 1.5: Robustness checks difference-in-differences

(a) Patents

	(1)	(2)	(3)	(4) Unweighted	(5) Weighted
Post 1987 x Substitutes	1.865***	0.904***	0.845***	1.583***	1.210***
	(0.072)	(0.092)	(0.092)	(0.076)	(0.096)
Log Count (lag 1)		0.559***	0.371***		
		(0.039)	(0.049)		
Log Count (lag 2)			0.270***		
			(0.047)		
Mean proportion of topic 1				2.088***	1.128*
				(0.779)	(0.619)
Mean proportion of topic 2				-0.199	0.124
				(0.584)	(0.554)
Mean proportion of topic 3				1.194***	1.212***
				(0.391)	(0.342)
Mean proportion of topic 4				0.321	0.868
				(0.610)	(0.552)
Mean proportion of topic 5				-0.424	0.495
				(1.132)	(0.789)
Year FE	Yes	Yes	Yes	Yes	Yes
Molecule FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.976	0.985	0.986	0.981	0.984
Observations	1288	1232	1176	1285	914

(b) Articles

	(1)	(2)	(3)	(4) Unweighted	(5) Weighted
Post 1987 x Substitutes	0.727***	0.508***	0.421***	0.266***	0.274***
	(0.068)	(0.063)	(0.060)	(0.058)	(0.058)
Log Count (lag 1)		0.348***	0.245***		
		(0.031)	(0.030)		
Log Count (lag 2)			0.297***		
			(0.031)		
Mean proportion of topic 1				1.513***	1.018***
				(0.432)	(0.363)
Mean proportion of topic 2				0.833**	1.096***
				(0.346)	(0.278)
Mean proportion of topic 3				1.108**	1.040**
				(0.481)	(0.409)
Mean proportion of topic 4				1.168***	1.172***
				(0.443)	(0.354)
Mean proportion of topic 5				0.939***	1.094***
				(0.359)	(0.296)
Year FE	Yes	Yes	Yes	Yes	Yes
Molecule FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.947	0.953	0.956	0.961	0.961
Observations	1680	1624	1568	1680	1680

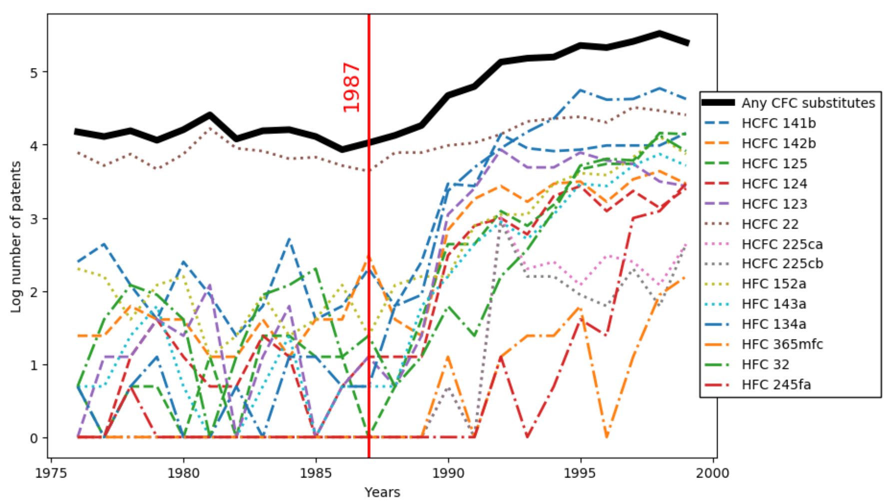


Figure 1.6: Patent counts in log for CFC substitute, individually and aggregated

Note: The graph illustrates the difference between considering the 14 molecules independently and considering them as one treated molecule. The thick line called "Substitutes (aggregated)" corresponds to the number of patents mentioning any of the 14 CFC substitutes. It is equivalent to considering the 14 compounds as one and only one molecule. I implement the synthetic control method on this "aggregated CFC substitute" because my objective is to estimate the effect of Montreal on research and innovation on any of the CFC subsitutes as opposed to any one in particular. It should be noted here that since the names of different CFC substitutes often appear simultaneously in the same documents, the individual time series of each CFC substitute are not independant from each other.

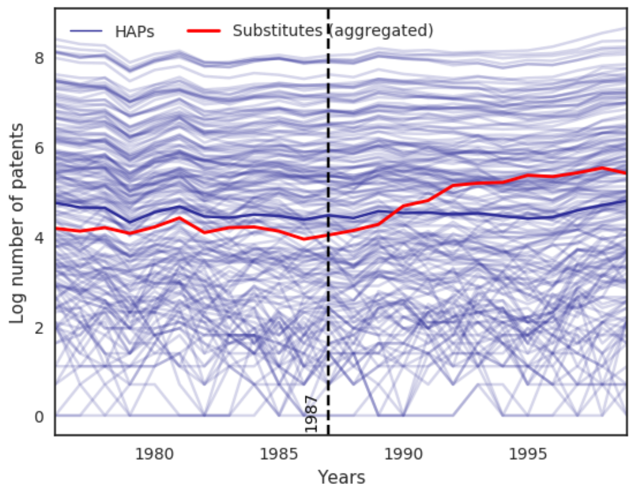
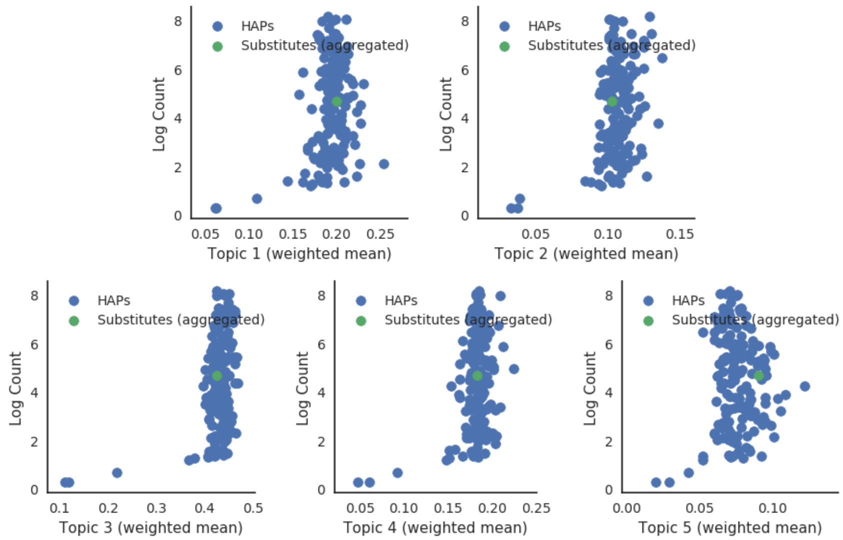
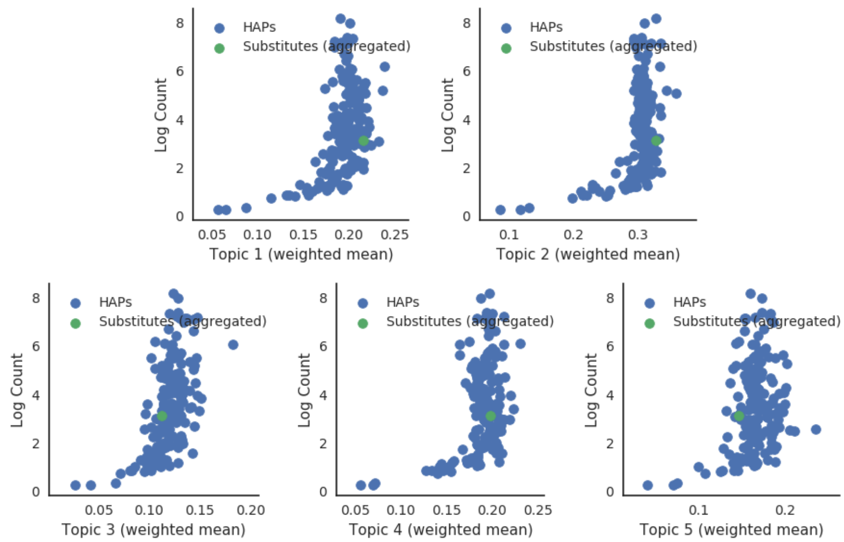


Figure 1.7: Patent counts in log for each HAP and for the aggregated CFC substitutes

Note: The graph illustrates the heterogeneity of HAP molecules. The thin lines correspond to the trends for each individual HAP while the thick HAP line corresponds to the mean counts for HAPs. We see that HAPs are a diverse group of molecules. In particular, some of them have log counts much higher than the aggregated CFC substitutes. The synthetic control method will allow to construct a better control group by using only the HAPs most similar to CFC substitutes.



(a) Patents



(b) Articles

Figure 1.8: Scatterplot of topics proportion and log count.

Note: The graphs illustrate the usefulness of topic proportions in the SCM. The scatter plots indicate that there are some clear outlier molecules: molecules with semantic contexts far from CFC substitutes. Implementing the SCM with topic proportions therefore provides a way of avoiding such molecules contribute to constructing a comparison unit. I implement the SCM in two different ways. First, I use the entire sample of HAPs as donor pool (168 units). Second, I create a "small" donor pool containing only the 20 HAPs that are closest to the aggregated CFC substitutes in terms of log counts and topic proportions. Implementing the SCM on a smaller donor pool allows for reducing the risk of overfitting and interpolation bias.

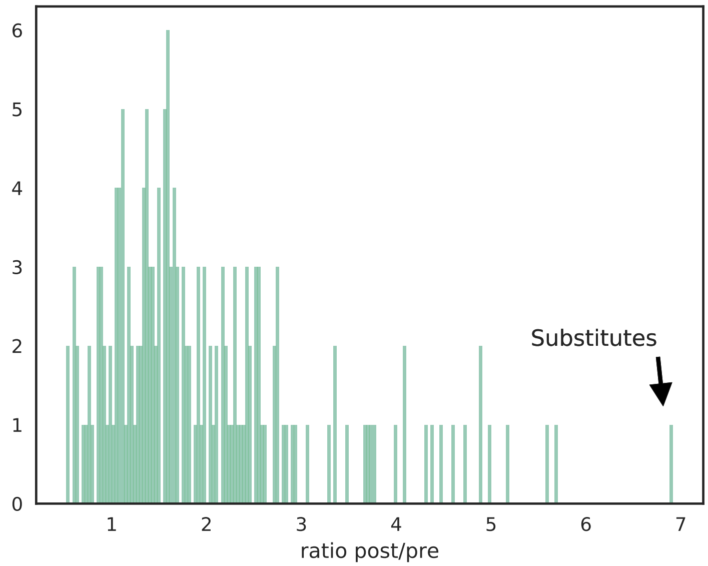


Figure 1.9: Distribution of post / pre RMSPE ratios for placebos for CFC substitutes
Note: The figure illustrates the ifnerence procedure for the SCM. The graph displays the distribution of post-RMPSE over pre-RMPSE for all placebo units. The figure shows that the ratio for CFC substitutes is clearly greater than all of the 168 other units. Hence the p-value in this case is 1/168.

Table 1.6: SCM results for CFC substitutes

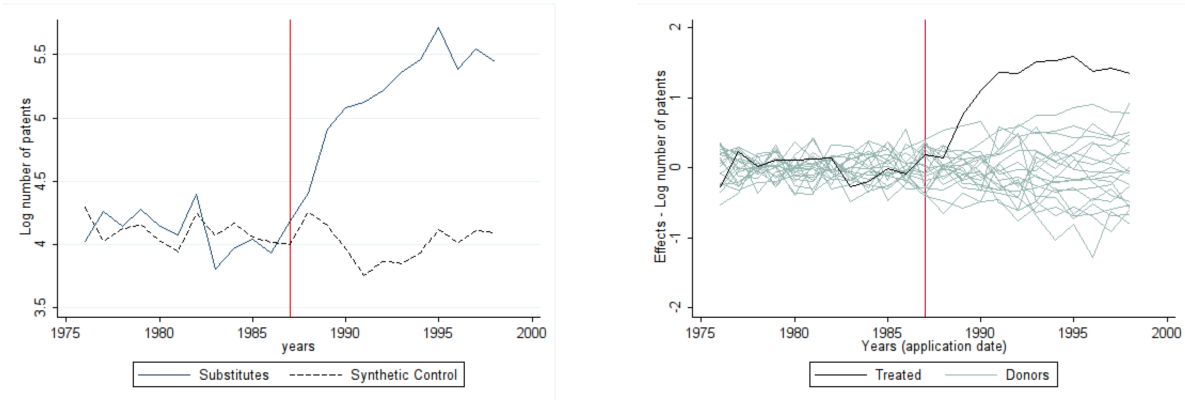
(a) Patents

Topic Means	Donor Pool	Pre RMSPE	p-value	ATE	Year
unweighted	whole sample	0.12	< 0.01	0.64	1990
weighted	whole sample	0.14	< 0.01	0.83	1990
unweighted	small pool	0.18	< 0.01	0.89	1990
weighted	small pool	0.32	0.11	0.99	1990

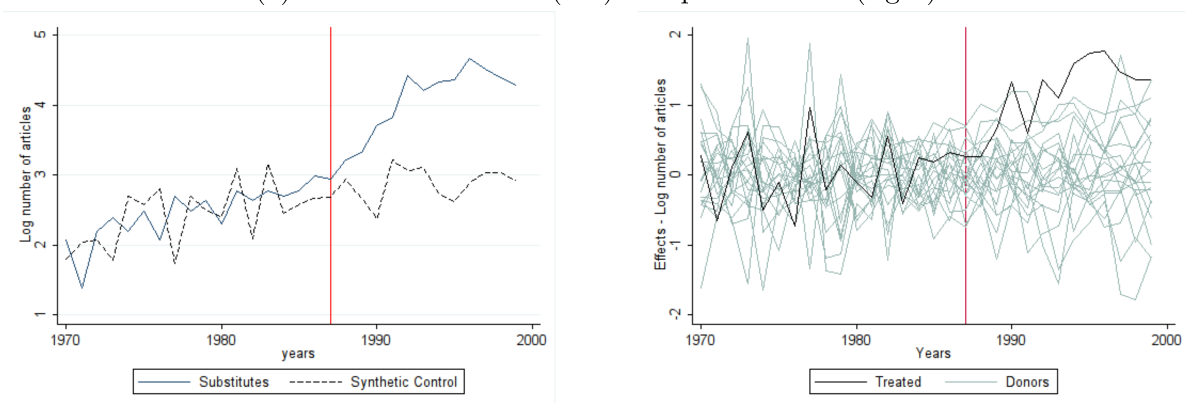
(b) Articles

Topic Means	Donor Pool	Pre RMSPE	p-value	ATE	Year
weighted	small pool	0.21	< 0.01	1.06	1990
unweighted	small pool	0.24	< 0.01	1.01	1992
weighted	whole sample	0.34	0.02	1.03	1990
unweighted	whole sample	0.35	< 0.01	1.19	1990

Note: The tables present the results of the main SCM specifications for patents and articles using either weighted or unweighted means of topic proportions and using either the whole sample and small pool of HAPs. The prefered specification to report the average treatment effect (ATE) uses the small pool of HAPs because it minimizes the risk of interpolation biaises and overfitting. It also uses weighted means of topic proportions because it yields a lower pre-RMSPE (pretreatment root mean squared prediction error) indicating that it provides a better counterfactual. For patents, the ATE of the prefered specification is 0.89, that is a 140% increase in patents compared to synthetic control. This corresponds to about 120 patents per year from 1988 to 2000. For articles, the ATE is 1.06, that is a 190% increase in patents compared to synthetic control. This corresponds to about 40 patents per year from 1988 to 2000. "Topic Means" indicates the procedure for aggregating the topic proportions at the molecule level. If "weighted", the calculated proportion of topic j for molecule i is the mean proportion of topic j across all documents mentioning molecule i, weighted by the number of times the molecule appears in the document. "Donor Pool" indicates what sample of HAPs is used in the SCM procedure. For "small pool", the sample of HAPs used corresponds to the twenty HAPs most similar to the treated unit in terms of counts and topic proportions before 1987. "Year" indicates the first year when the treatment effect is significant at the 10% level.



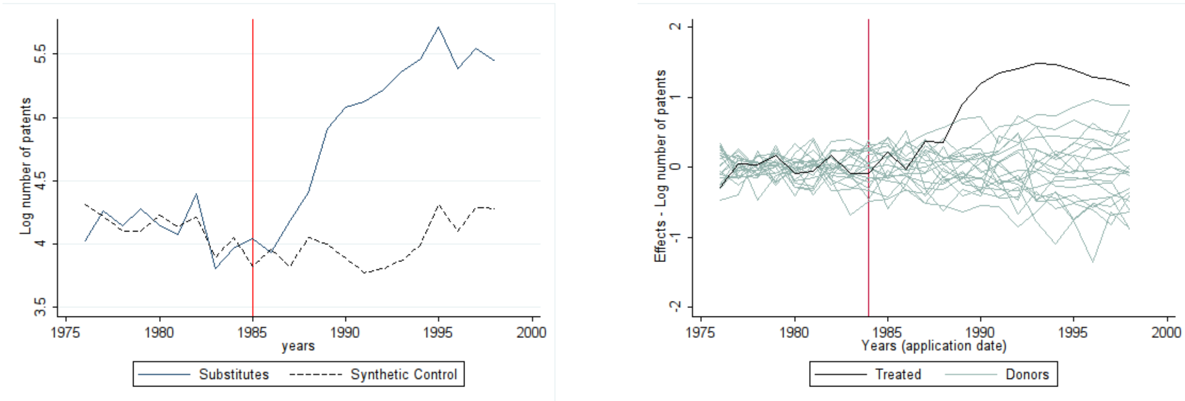
(a) Patents: raw effect (left) and placebo tests (right)



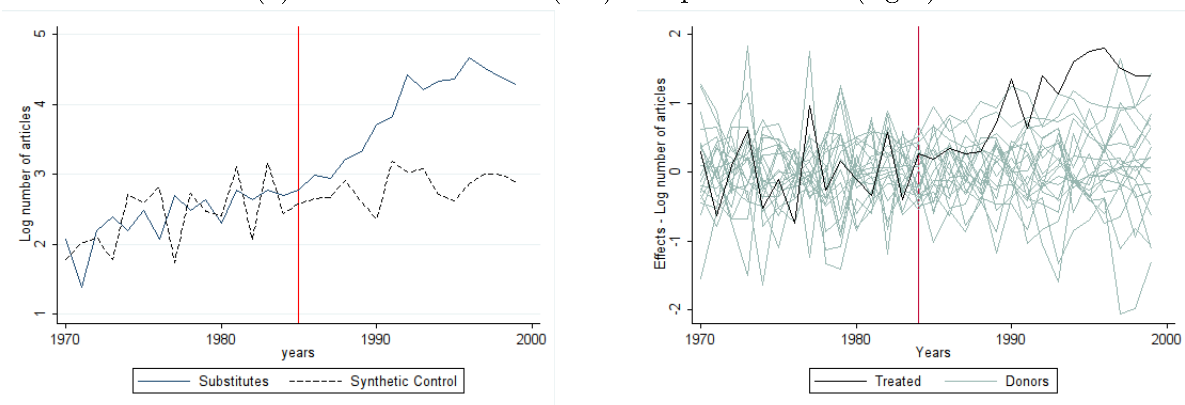
(b) Articles: raw effect (left) and placebo tests (right)

Figure 1.10: SCM graphs for CFC substitutes

Note: The graphs correspond to SCM implementation for the prefered specification, that is when the SCM is implemented with log counts using the small pool of HAPs and weighted means of topic proportions. The graphs on the left-hand side show the raw effect, that is the observed time series of the treated group along with the time series of the constructed control. On the right-hand sides are shown the placebo tests, the non-parametric tests to evaluate the significance of the results; black lines show the relative effect on the treated group relative to the control group, while each gray line is a placebo test performed on an unit drawn from the donor pool. The effect on CFC substitutes appears large and significant for both patents and articles. Placebo tests confirm that the effect is significant starting a few years after 1987; indeed the black line rises above most other lines as from 1990. This might correspond to a natural lag time between the redirection of research activities towards CFC substitutes and the publication or patenting of such work.



(a) Patents: raw effect (left) and placebo tests (right)



(b) Articles: raw effect (left) and placebo tests (right)

Figure 1.11: SCM graphs for CFC substitutes assuming anticipation

Note: The graphs display the results of the synthetic control method for substitutes for patents and articles assuming anticipation. For these experiments, the treatment year is redefined as 1985 and the synthetic control constructed using data up to 1982. Results are similar to previous SCM experiments. Specifically, there are no take-offs before 1990. The graphs corresponds to SCM implementations that yielded the lowest pre-RMSPE. That is, for both patents and articles, the SCM uses log count and weighted means of topic proportions. The graphs on the left-hand side represent the raw effect, that is the observed time series of the treated group along with the time series of the constructed control. On the right-hand sides are shown the placebo tests, the non-parametric tests to evaluate the significance of the results; black lines show the effect on the treated group relative to the control group, while each gray line is a placebo test performed on an unit drawn from the donor pool.

Table 1.7: Top four HAPs contributing to the synthetic control

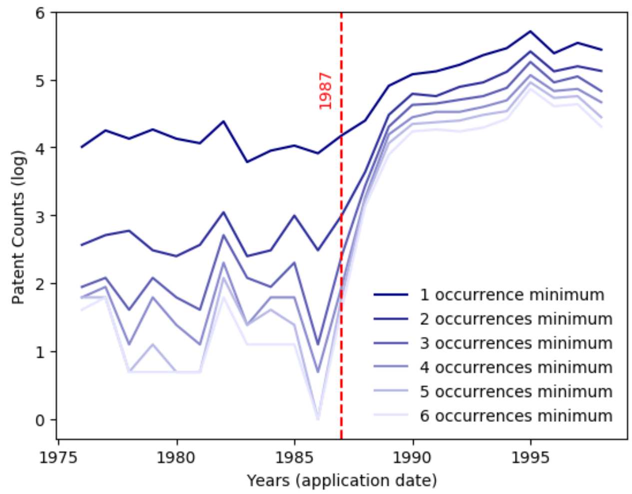
(a) Patents

Molecule	Weight	Description
Pentachlorophenol	0.33	Used as a wood preservative; Used for the formulation of fungicidal and insecticidal solutions and for incorporation into other pesticide products.
p-Xylenes	0.20	Used in the production of styrene. and as solvents in products such as paints and coatings, and are blended into gasoline.
Ethyl chloride	0.12	Used production of ethyl cellulose, use as a solvent, refrigerant, and topical anesthetic, in the manufacture of dyes, chemicals, and pharmaceuticals. As an anti-knock additive to leaded gasoline
3,3-Dimethoxybenzidine	0.11	Used as an intermediate for the production of dyes and pigments

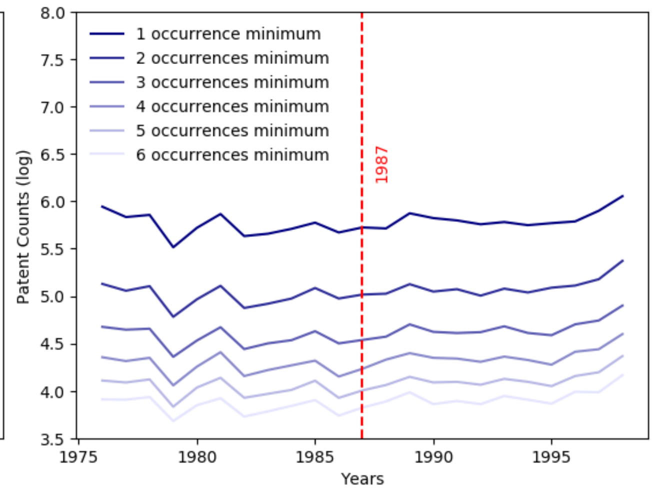
(b) Articles

Molecule	Weight	Description
Ethyl acrylate	0.48	Used in the manufacture of water-based latex paints and adhesives, textile and paper coatings, leather finish resins, and in the production of acrylic fibers
beta-Propiolactone	0.26	Used for vaccines, tissue grafts, surgical instruments, and enzymes, as a sterilant of blood plasma, water, milk, and nutrient broth, and as a vapor-phase disinfectant in enclosed spaces.
Dimethyl phthalate	0.24	Used in solid rocket propellants, lacquers, plastics, safety glasses, rubber coating agents, molding powders, insect repellants, and pesticides
1,1,2,2-Tetrachloroethane	0.01	Used as a solvent, in cleaning and degreasing metals, in paint removers, varnishes and lacquers, in photographic films, as an extractant for oils and fats, and in pesticides.

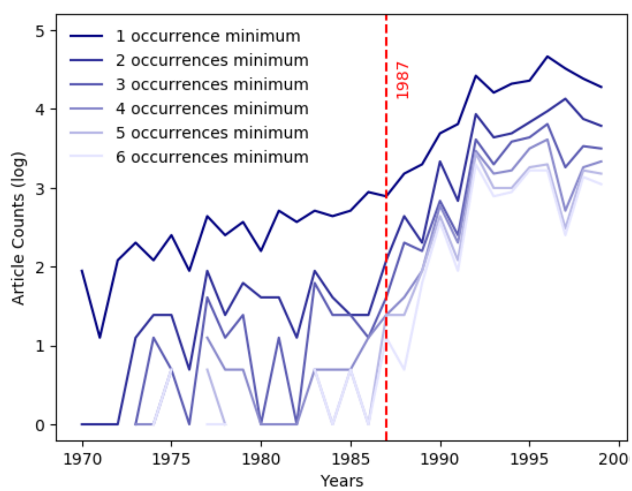
Note: The tables describe the top four HAPs entering the synthetic control for the prefered SCM specifications (small pool, weighted means of topic proportions). The information displayed in the "Description" column was collected from the EPA website.



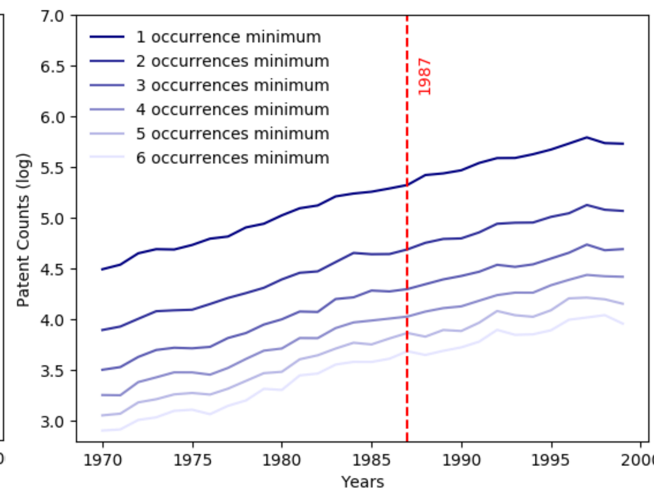
(a) Patents - CFC substitutes (aggregate)



(b) Patents - HAPs (average)



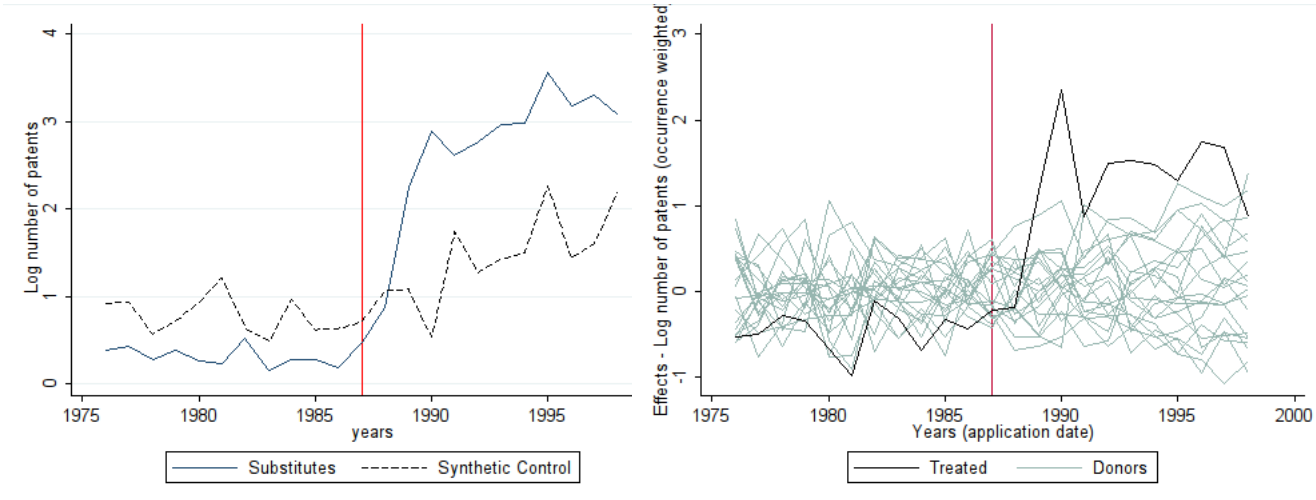
(c) Articles - CFC substitutes (aggregate)



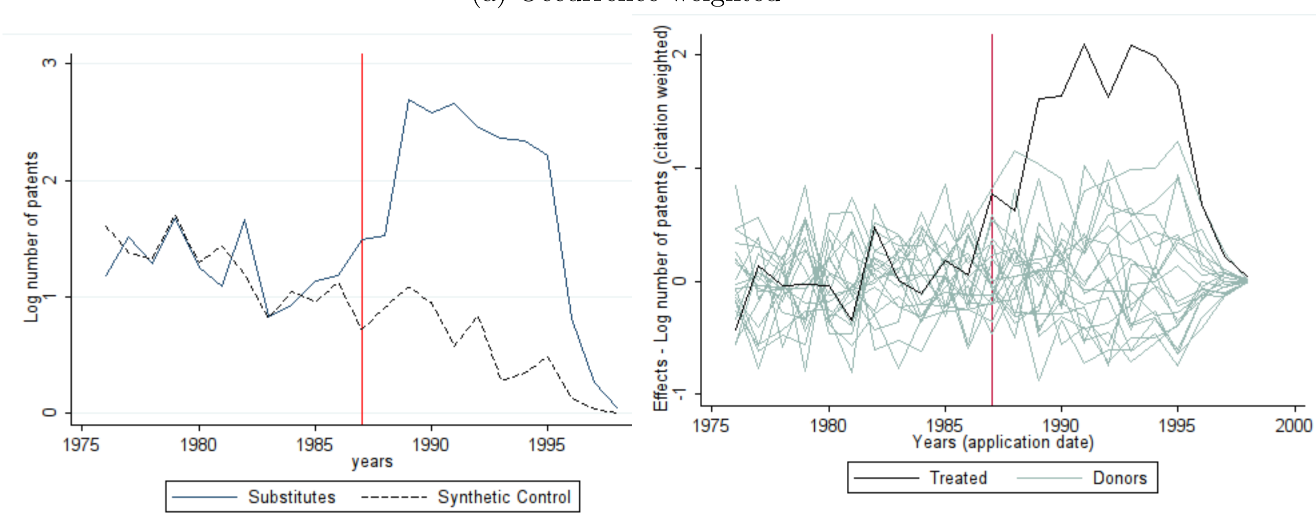
(d) Articles - HAPs (average)

Figure 1.12: Robustness check: counts with several thresholds of molecule occurrences

Note: The graphs illustrate that focusing on patents and articles that contain more than just one occurrence of molecule would change little to the main analysis. As we increase the occurrence threshold, the trend for the average HAPs remain very similar; only levels decrease. For CFC substitutes, focusing only on patents with greater number of occurrences exarcerbates the differential between the pre and post trends.



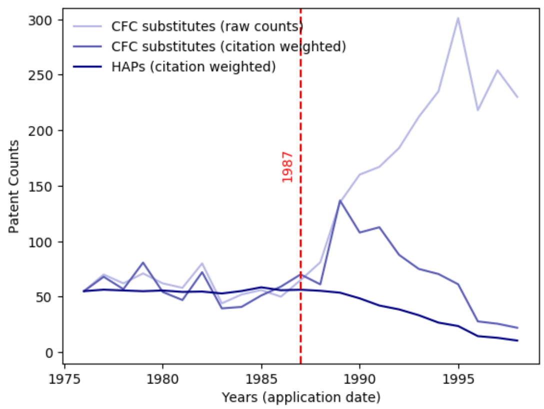
(a) Occurrence weighted



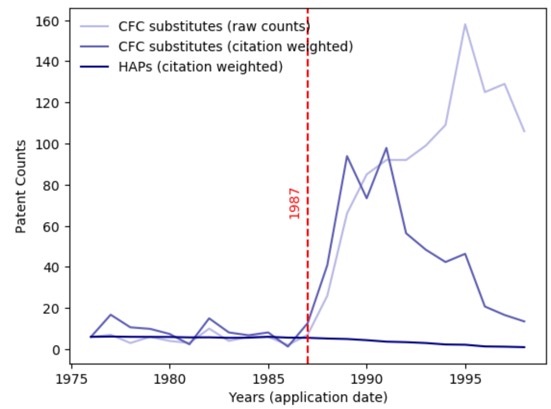
(b) Occurrence and citation weighted

Figure 1.13: Robustness check: SCM with counts weighted by occurrences and citations

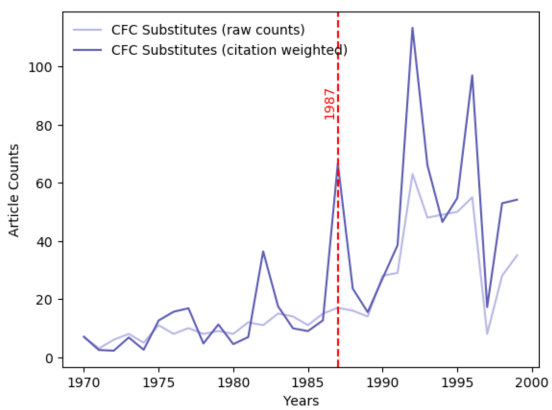
Note: These figures show that implementing the SCM using patent counts weighted by molecule occurences and patent citation does not alter the main conclusions.



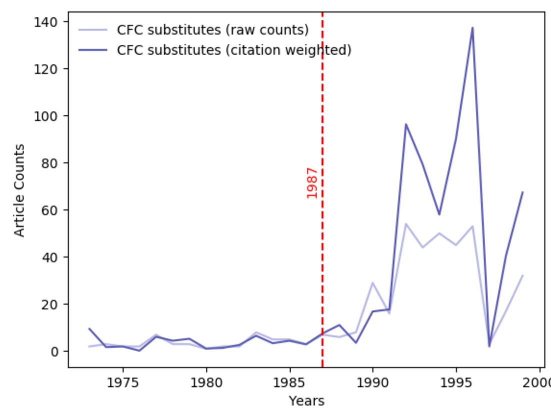
(a) Patents - one occurrence



(b) Patents - three occurrences



(c) Articles - one occurrence



(d) Articles - three occurrences

Figure 1.14: Time series of citation weighted counts

Note: The graphs illustrate that the most cited articles and patents were published after 1987. The graphs on the left-hand side include any document that mention at least one occurence of a molecule. To test the robustness of this findings, I plot similar graphs but for patents and articles that mention at least three occurences on the figures on the right-hand side. I find that highly cited patents and articles are even more so concentrated after 1987. Collecting citation data for HAPs is undergoing and limited by quotas on the Elsevier API.

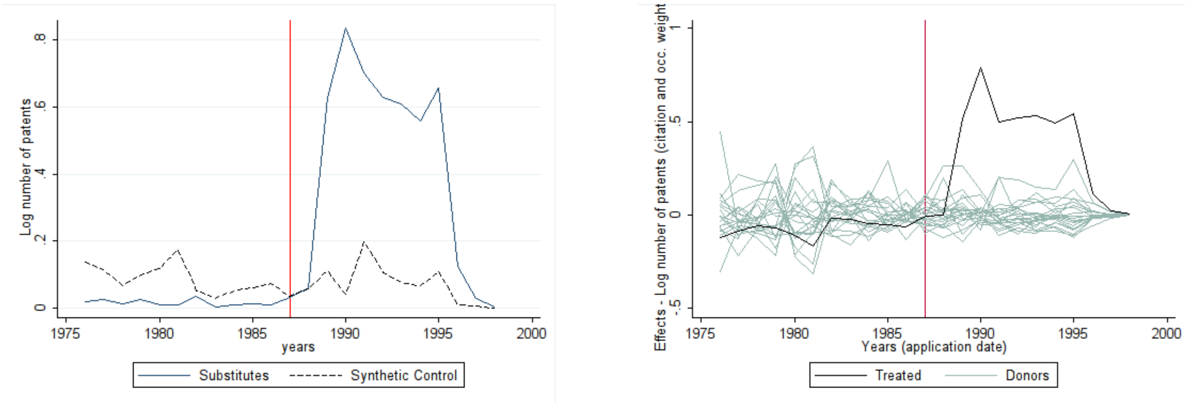
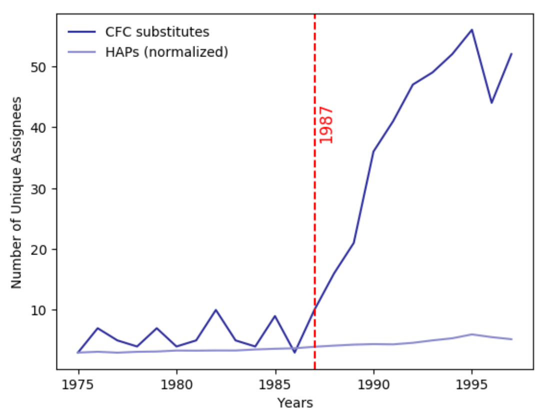
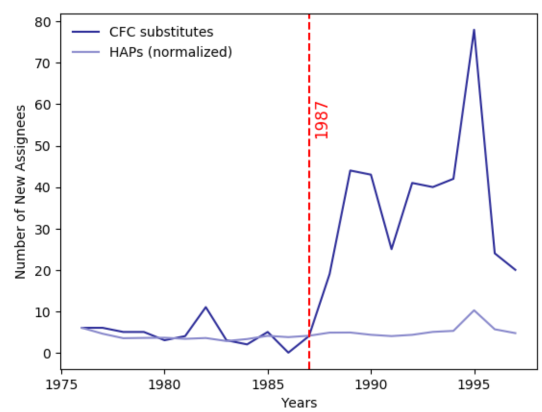


Figure 1.15: SCM graphs using citation weighted patent counts

Note: The graphs illustrate the robustness of the main results using citation weighted patent counts.



(a) Unique assignees



(b) New entrants

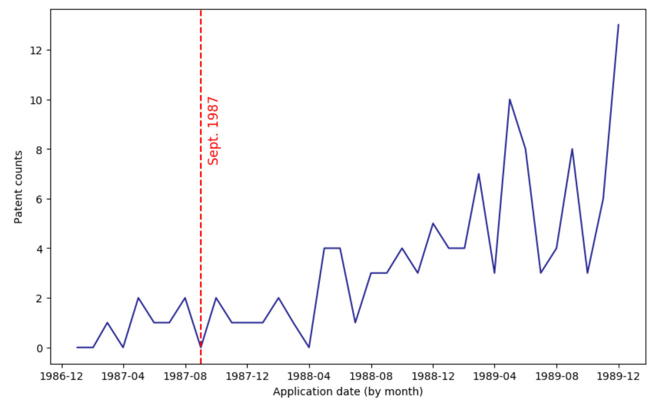
Figure 1.16: Number of unique and "new entrant" patent assignees

Note: Figure 1.16a displays the yearly number of unique assignees with patents mentioning CFC substitutes and HAPs. It indicates that the likely presence of new entrants in the post 1987 period. Figure 1.16b displays the yearly number of assignees that are "new", meaning it is the first time they appear in the data with a patent mentioning CFC substitutes and HAPs. The figure confirms that, after 1987, many firms with no prior experience on CFC substitutes begin patenting. In both figures, only patents with at least 3 molecule occurrences are kept in the sample.

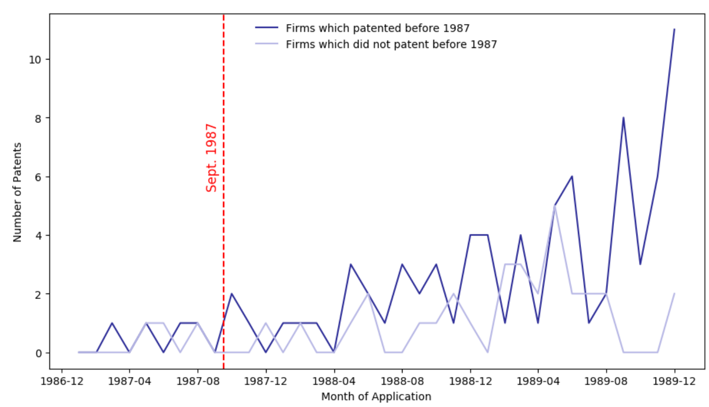
Table 1.8: Titles of the 10 most cited articles mentioning CFC substitutes

Title	Year	Cited By
Methods for the synthesis of gem-difluoromethylene compounds	1996	333
A new, efficient and environmentally benign system for car air-conditioning	1993	255
High-pressure fluid-phase equilibria: Experimental methods and systems investigated (1988-1993)	1995	227
Evaporation heat transfer and pressure drop of refrigerant R-134a in a small pipe	1998	211
Gas and vapor transport properties of amorphous perfluorinated copolymer membranes based on 2,2-bistrifluoromethyl-4,5-difluoro-1,3-dioxole/tetrafluoroethylene	1996	184
Boiling of new refrigerants: A state-of-the-art review	1996	144
Condensation heat transfer and pressure drop of refrigerant R-134a in a plate heat exchanger	1999	142
Thermochemical and chemical kinetic data for fluorinated hydrocarbons	1995	130
Supercritical fluid extraction in environmental analysis	1993	121
A kinetic study of the reaction of chlorine atoms with CF3CHCl2, CF3CH2F, CFCl2CH3, CF2ClCH3, CHF2CH3, CH3D, CH2D2, CHD3, CD4, and CD3Cl at 2952 K	1992	113

Note: The table displays the titles of the most cited articles mentioning CFC substitutes. Only articles with three molecule occurrences in the text were kept in the sample. We note that these articles, as expected, seem to focus on chemical and physical characteristics of CFC substitutes ("boiling", "evaporation", "pressure" etc...).



(a) All assignees



(b) Old vs. new entrants

Figure 1.17: Monthly counts for patents mentioning CFC substitutes

Note: The graphs show the monthly trends in count of patents mentioning CFC substitutes. It is possible that some firms started working on CFC substitutes before Montreal without seeking patent protection. If those firms has achieved significant advnaces in developping CFC substitutes, we would expect a one-time increase in patent counts in the immediate aftermaths of Montreal. We see on the first graph that this is not the case. Furthermore, if the extent of R&D efforts provided before Montreal was the key driver to the post-Montreal increase in patenting, we should observe major differences in the patenting trends of old and new entrants. On the second graph, I present trends for assignees that never obtained any patent mentioning CFC substitutes before 1987 and those who did. Although a gap seem to build up over time, trends look mostly similar. Only patents with at least 3 molecule occurrences are kept in the sample. The year used is the application year. The period "Before 1987" includes the year 1987.

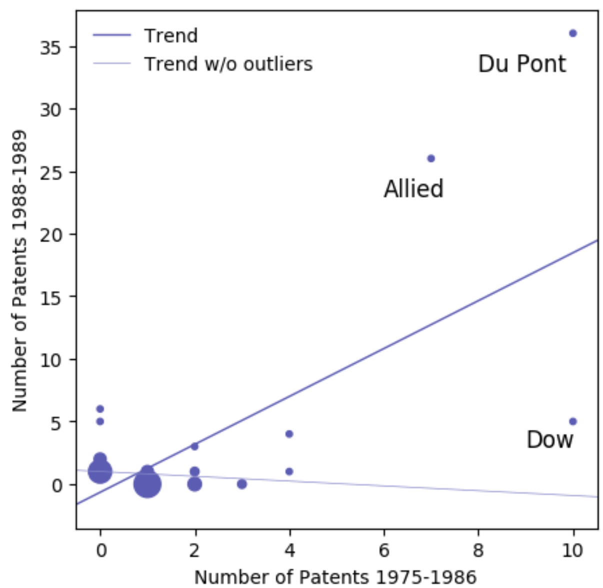
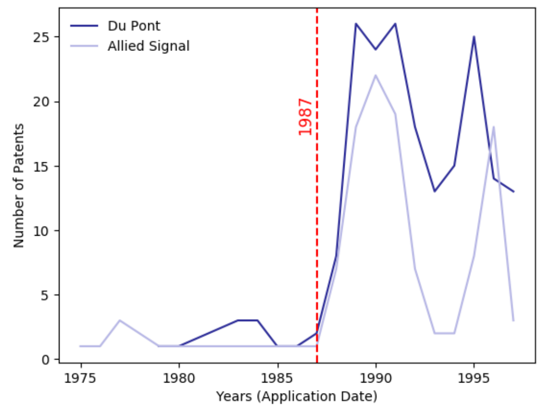
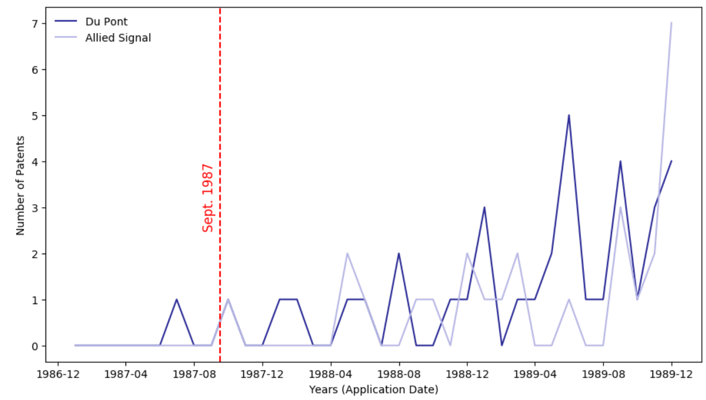


Figure 1.18: Scatterplot of patenting activity before and after 1987

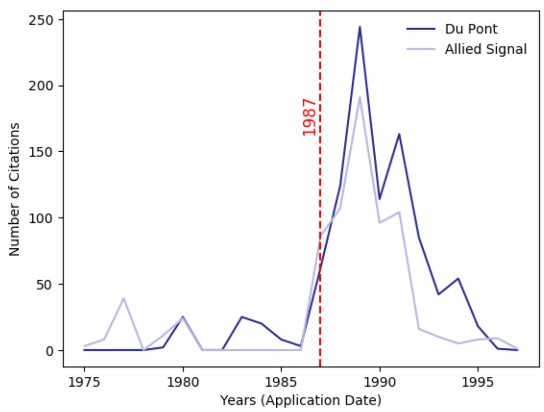
Note: The figure shows that, on average, firms with more patents before 1986 tend to also have more patents in the immediat aftermaths of Montreal (1988 and 1989). But, the graph illustrates that this effect is largely driven by three outliers: Du Pont, Allied and Dow. Excluding these three firms, there is no clear correlations between patenting prior to 1987 and patenting in the immediat aftermaths of Montreal. The size of the dot is proportional to the number of firms. Only patents with at least 3 molecule occurrences are kept in the sample. The year used is the application year.



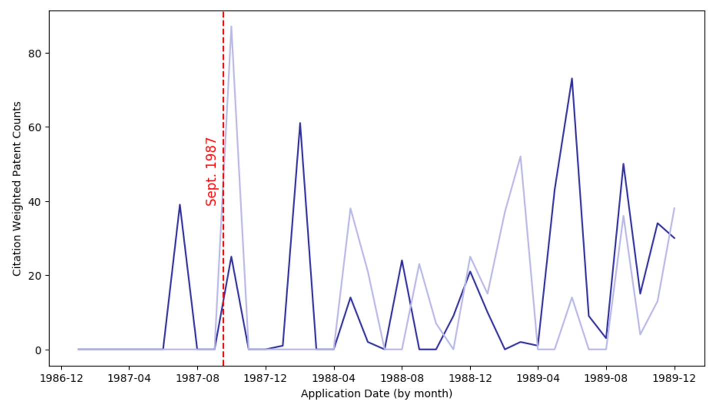
(a) Yearly Counts



(b) Monthly Counts



(c) Yearly Citation Weighted Counts



(d) Monthly Citation Weighted Counts

Figure 1.19: Patent counts for Du Pont and Allied

Note: Figure 1.19a shows that most patents granted to Du Pont and Allied were applied for after 1989. Figure 1.19b shows that there is no sudden peak patenting right after Montreal. Instead we observe a gradual ramping up of patenting activity. Figure 1.19c illustrates that the patents granted to Du Pont and Allied which received the greatest number of citations mostly originate from 1989 to 1991. Figure 1.19d indicates, however, that, in the weeks that followed Montreal, both Du Pont and Allied applied for patents that would go on receiving a high number of citations. Only patents with at least 3 occurrences of a molecule are retained in the sample.

Chapter 2

Passive Learning and Incentivized Communication: A Randomized Controlled Trial in India

Yonas Alem and Eugenie Dugoua

2.1 Introduction

Economic growth theories portray technological progress as the engine of economic development and prosperity. The recent version of this theory uses endogenous growth models to highlight the important role of social learning in technology diffusion (Acemoglu 2009; Aghion et al. 1997; Barro et al. 2004; Lucas 1988; Romer 1986). Economic growth in this set-up is characterized as endogenously driven through investment in human capital, knowledge and innovation. Profit maximizing firms invest, learn by doing and learn from each other through knowledge spillovers; these processes induce smooth technological diffusion in the economy. The theory was later applied to understand technological innovation and diffusion in agriculture in developing countries (Bandiera et al. 2006; Bardhan et al. 1999; Conley et al. 2010; Foster et al. 1995). Using state-of-the-art empirical strategies, this strand of literature identifies the role of social networks in promoting social learning, adoption and diffusion of new agricultural technologies.

One feature of earlier studies on the role of social networks is the assumption of "passive learning", a situation in which peers learn about new technologies from their peers without cost. However, in recent research, BenYishay et al. (2014) show that the power of social networks in diffusion of new technologies could be enhanced by incentivizing information communication. In this paper, we attempt to shed light on the role of incentivizing information communication by one's network members or peers on willingness to pay (WTP) for new technology using a randomized controlled trial (RCT) in India. Motivated by theories of intra-household decision-making, we also investigate the role of gender in information communication and willingness to pay for the new technology.

We collaborated with a local organization and distributed a new solar-powered lantern to households in Gonda district, in the Uttar Pradesh state of India. The solar lanterns are durable, multipurpose, and convenient to use. They sold for 1,200 rupees (USD 18.5) in Lucknow, the capital of Uttar Pradesh state at the time of the fieldwork (Fall, 2015). Notably, the lanterns have a mobile-charging feature which allows the user to charge a mobile phone.

The study area is still non-electrified and households did not have knowledge about the solar lanterns prior to the study. We randomly selected 200 "seed" individuals, half of them male and half of them female, to whom we offered the solar lantern for participating in the study. Each seed household gave three names of peers (friends or relatives), and these were randomly assigned into a "network treatment", a "communication treatment" and a "control group". We elicited willingness to pay for the solar lanterns from the control group immediately after interviewing the seed household, using the Becker-Degroot-Marschak (BDM) method (Becker et al. 1964). In the network group, the subjects, who were designated as friends by the seed, were interviewed 30 days after the seed received the solar lantern to elicit their willingness to pay. We refer to the learning captured through this process as "passive learning". In the communication group, the 30-day delay was followed by a tea meeting at which the seed presented the solar lantern and shared his or her experience with the friend, in return for a payment of 100 rupees (USD 1.54).[1] We refer to the learning captured through this process as "incentivized communication".

The results show that peers who very likely learned about the solar lantern through their relationship with the seed household are on average willing to pay 120 rupees more than the control group a month after the lanterns were distributed. Peers who were invited to a demonstration tea meeting by the seed households a month after the lanterns were distributed, on the other hand, are willing to pay 190 rupees more than the control group. With a mean WTP of 134 in the control group, the proportional treatment effects are 90% and 145%, respectively. Both treatment effects appear to be large. It is notable that the passive learning treatment effect almost doubled WTP, whereas incentivized communication added another 55 percentage points increase in the treatment effect.

This paper is broadly related to a body of research in economics on the impact of peers on outcomes. This strand of literature, focusing mostly on developed countries, investigates the impact of peers or friends on several outcome variables of interest, including educational

[1] At the time of the survey, 1 USD = 65 rupees.

achievement (e.g., Angrist et al. 2002; Figlio 2005; Hoxby 2000; Sacerdote 2001; Zimmerman 2003), market and health outcomes (e.g., Kling et al. 2007; Munshi 2003), labor productivity and consumption (e.g., Mas et al. 2009; Mobius et al. 2005) and adoption of technology (Oster et al. 2012). The extent of peer effects has also been examined in the development economics literature, largely to explain agricultural technology adoption (Bandiera et al. 2006; Bardhan et al. 1999; Conley et al. 2010; Foster et al. 1995). A particularly important observation in this literature is that modern agricultural technologies significantly promote yield, but their adoption or uptake rate has been disappointingly low. These studies show that, when farmers consider adopting new technologies, they are likely to trust recommendations from their peers, friends, or members of their social network who have experienced the technology, rather than from others external to their community.

BenYishay et al. 2014 investigate social learning further by designing a randomized controlled trial in rural Malawi to vary the method of dissemination of information about two agricultural technologies that promote yield - pit planting and Chinese composting. These authors specifically investigate whether provision of performance-based rewards to those who communicate about the new technologies results in increased diffusion of the technologies. Among the three types of information communicators they chose - government-employed extension workers, lead farmers, and peer farmers - adoption of the technologies by others was much more likely in response to the information provided by peer farmers. Our paper adds to this literature by disentangling the magnitudes of "passive learning", i.e., learning from others without cost, and "incentivized communication", i.e., learning from others through improved quality of information, on willingness to adopt and pay for the new technology. Unlike agricultural technologies which involve uncertainty and take time to capture their payoff, the solar lantern we consider is easy to use and multi-purpose, and it is easy to assess its payoffs with greater certainty in a short time. Our design also allows us to aggregate revealed WTP, a figure important for policymakers and other stakeholders to design optimal subsidy and cost reduction strategies to encourage diffusion of the technology in cases when average WTP is lower than average cost.

The major challenge in identifying the impact of peers on adoption of new technologies, even after tackling endogeneity through a randomized assignment, is understanding the mechanisms that drive the observed results. It may be that peers imitate each other rather than learning from each other about the benefits of the new technology or learning how to operate the technology (Oster et al. 2012). In order to shed light on the possible mechanisms, we collected detailed information on familiarity with solar lanterns, perception about their benefit, estimated market value, etc. As expected, we find that both the network and the communication groups are likely to have seen a solar lantern before the date of the WTP experiment, and they are much more likely to know someone who owns a lantern, compared to the control group. We also find that, compared to the control group, subjects in both treatment groups believe that the solar lantern needs proper maintenance in order to function properly and they estimate its market price to be higher. We also observe that subjects initially don't think solar lanterns are worth more than kerosene lamps, which are the most common sources of lighting in the study area. However, as they see a friend taking care of the solar panel through which the lantern is powered, the power of the light coming out the lantern, and the mobile phone charging function, they estimate the market price of the lantern to be higher. Consequently they are willing to pay more for the lantern. These results suggest that learning both how to operate the technology and the benefits provided by the technology drive the high WTP the treatment groups reveal, notably to a larger extent that of the communications group's.

The paper also speaks to the emerging literature on electrification in developing countries (Dinkelman 2011; Dugoua et al. 2014; Furukawa 2014; Grimm et al. 2014; Lee et al. 2016a,b), an area of research that overlaps with development and energy economics. The current level of electrification in developing regions such as Sub-Saharan Africa, South Asia, and Latin America remains low (International Energy Agency 2014). Extending the grid to the most rural regions requires high levels of investment that are often difficult to secure by governments. Solar power serves as a decentralized solution to the problem of energy poverty, and is slowly diffusing throughout rural Africa and rural South Asia (Sandwell et al. 2017). However, tight household budget constraints, poor product quality and little local expertise in photovoltaic technologies have been hindering faster adoption.[2] In addition, given the increased need to reduce greenhouse gas emission from the energy sector, exploring the role of solar-powered lighting equipment, which emits no greenhouse gas would have large benefits to society at large. From a public policy point of view, the findings from this paper will provide useful information on willingness to uptake such technologies and the factors that drive their quick diffusion.

The rest of the paper is organized as follows. Section 2 discusses the relationship of the current paper to existing literature. Section 3 lays out our key hypotheses about willingness to pay for solar lanterns. Section 4 describes the design and procedure of the randomized controlled trial, with results of the randomization checks. Section 5 presents the key empirical results. Section 6 concludes.

2.2 Relationship to Existing Literature

This paper contributes to a large and growing literature on the role of peers - co-workers, friends and acquaintances - on behavior and outcomes that builds off the work of Sacerdote 2001, Hoxby 2000, Munshi 2003, and Mobius et al. 2005. Friends and members of social networks influence one's beliefs and consequently decisions. These studies, almost exclusively focused in developed countries, document the impact of peers on one's educational achievements, labor productivity, and consumption behavior. Roommates affect one's freshman GPA and the decision to join social organizations, and classmates influence reading scores in elementary schools in the United States (Hoxby 2000; Sacerdote 2001). Peers and networks members help Mexican migrants in the United States find higher-paying jobs (Munshi 2003)

[2]See Karakaya et al. 2015 for a recent systematic review of the literature on barriers to the adoption of photovoltaic technologies in developing countries.

and have as large an effect as advertising on consumer demand (Mobius et al. 2005). Other studies in similar settings (e.g., Angrist et al. 2002; Figlio 2005; Kling et al. 2007; Mas et al. 2009; Zimmerman 2003) further document the role of peers in influencing one's behavior and decisions.

There are studies (e.g., Bandiera et al. 2006; Conley et al. 2010; Foster et al. 1995) investigating the role of peers in social networks in adoption and diffusion of productivity-enhancing modern agricultural technologies in developing countries. These studies were mainly motivated by the fact that modern agricultural technologies significantly promote yield and improve welfare, but their adoption and diffusion rates have been sub-optimally slow. Adoption of a new agricultural technology by a farmer is a social process because it generates knowledge to all her peers and increases their expected yield (Bardhan et al. 1999). This strand of literature implies that farmers in developing countries are likely to trust recommendations by fellow farmers more than by those from other people external to their community. In view of this, social networks play a significant role in diffusion of new technologies. Outside an agricultural set-up, more recently Oster et al. (2012) investigate the role of peer effects in adoption of menstrual cups by school girls in Nepal and document a strong effect on learning how to use the technology.

There are methodological challenges in identifying the impact of social networks on technology adoption using observational data. First, when two friends are both adopting a certain technology, it is difficult to distinguish whether it is because the two friends learn from each other or because individuals who are open to trying out a new technology also have friends with similar characteristics that are unobservable (Manski 1993). Second, it is difficult to precisely define the social network of an adopter of a new technology and even so, it may be that individuals are just imitating each other rather than learning from each other (Conley et al. 2010). Recent studies used the method of randomization to tackle these identification problems (Duflo et al. 2003, 2011; Godlonton et al. 2012; Kremer et al. 2007, 2008; Miguel et al. 2004; Oster et al. 2012; Rao et al. 2007; Sacerdote 2001).

A key feature of previous studies on the role of peers on adoption of new technologies (Bandiera et al. 2006; Conley et al. 2010; Oster et al. 2012) is the implicit assumption of learning from peers without a cost, i.e., "passive learning" (BenYishay et al. 2014). New technologies could be adopted and diffused faster if peers who communicate information about the new technology are rewarded. This is the key argument by BenYishay et al. (ibid.) who design a randomized controlled trial to vary the method of dissemination for two agricultural technologies - pit planting and Chinese composting - which are believed to improve maize yield in rural Malawi. These authors confirm the importance of social networks in diffusion of agricultural technologies, but argue that their power can be significantly improved by remunerating the peer who adopts the technology and makes a conscious effort to communicate and convince other farmers.

Our paper contributes to this literature in three main ways. First, this paper is the first to examine the impact of rewarding communication about a new technology on willingness to pay - as opposed to a binary measure of adoption. We clearly identify the impact and magnitude on WTP of both passive networks and incentivized communication by peers about a new solar lantern technology, using a randomized controlled trial. This distinction is important because estimating average willingness to pay allows policymakers to estimate whether new technologies could be distributed profitably and the amount of resources required to speed up adoption and diffusion in case revealed WTP is lower than the cost of the new technology. Second, unlike agricultural technologies, which take time to observe their benefit and involve substantial uncertainty, solar lanterns are easy technologies to learn about in a short period of time. As a result, biophysical and climatic factors, which seem to differ markedly even between closely located farms, would not be confounded with the decision to adopt and WTP for the technology. Third, we consider a technology which is not only quick to learn about, but also has a significant welfare effect on all members of households. The current rate of electrification in developing regions of the world is very low and households very often use kerosene lamps for lighting. Kerosene lamps have been documented to generate indoor air pollution and adversely affect health outcomes of members, pose a risk of burns and fires, emit hazardous greenhouse gases, and require rural households to regularly travel long distance to buy kerosene (Lam et al. 2012). The solar lanterns that we randomly distributed are, among other things, multi-purpose, affordable, and reasonably-priced, with a significant potential to enhance health outcomes of all household members, reduce greenhouse gas emissions and help children allocate more time to studying.

2.3 Conceptual Framework

Drawing on Bandiera et al. 2006; Bardhan et al. 1999; BenYishay et al. 2014; Conley et al. 2010; Foster et al. 1995, we now lay out a brief motivating framework for interpreting the main results. We begin by defining the following treatments:

- In the *network treatment* group, subjects observe the use of a new technology by others without incentivized communication. Thus, learning from others is passive.
- In the *communication treatment* group, subjects both observe the use of new technology by others and receive direct communication about the properties of the new technology just before WTP is elicited. Thus, learning from others is considered to be 'active'.

To test the presence of social learning – that is, learning from others – in agriculture, these studies make use of the "target-input" model proposed by Wilson (1975) and Jovanovic et al. (1994). According to this model, the farmer knows the basic form of the new technology (e.g., an improved seed) with certainty, but does not know the target level, which is assumed to be random. Farm profit is inversely related to the difference between the actual level of input applied and the target level. The farmer realizes what the actual level of input should have been only after the input has been applied and output has been realized. As a result, the farmer learns about the new technology over time through learning-by-doing.

In the target-input model, individuals can also learn from each other's experience when they share similar distribution of the input target. Assume that two farmers belong to a certain social network and share information with each other or costlessly observe each other's input choice. In each period, farmers use Bayes' rule to update their prior belief on the variance of the optimal input level, making use of information from their own experience and the experience of their network members. Thus, adoption of a new technology in this model is a social process because its adoption by an individual generates information spillover to all her peers, which increases their expected welfare in the future (Bardhan et al. 1999). Diffusion of solar lanterns can be modelled using the social learning framework because peers of seed households observe (without any cost) the service provided by the lanterns and immediately update their belief about the quality of the lanterns. Consequently, these individuals would be willing to pay more than those who did not have prior information about the lanterns.

Hypothesis 1. *The network treatment increases willingness to pay.*

An important extension of the 'target-input" model by **Benymodddb14** is that the member of the social network who communicates information about the new technology, i.e., the "communicator" knows the optimal level of the technology. However, it would be costly to transfer her knowledge about the new technology to other farmers. If there is an intervention that rewards the information communicator based on what proportion of farmers adopted the new technology as a result of the communicator's efforts, diffusion of the technology may occur much faster. Such incentives induce the communicator to make a conscious effort and bear the cost of communication and transmitting information about the new technology to others (BenYishay et al. 2014). As a result, others will learn about the new technology and adopt it much more quickly than the case of unincentivized communication through ordinary social networks. In our case, rewarding seed households to invite one of their randomly selected peers for a tea meeting after the seed household used the solar lanterns for a month is expected to result in transmission of more accurate information. As a result, peers who have been provided detailed information about the attributes of the solar lanterns in such a way are likely to pay more for the lanterns than peers who were not invited for the tea meeting (the network treatment group).

Hypothesis 2. *The communication treatment increases willingness to pay more than the network treatment.*

Another aim of our RCT is testing the role of gender in communication about a new technology. Early studies (Bourguignon et al. 2009; Browning et al. 1998; Chiappori 1992; Chiappori et al. 2002) from industrialized countries show that, although members of a household (most importantly, couples) often have different preferences and intra-household bargaining power, they still achieve Pareto-efficient outcomes in household decision-making. However, studies in developing countries document rejection of Pareto-efficiency in household decision-making, most importantly because of differences in preferences and intra-household bargaining power between husbands and wives. Udry (1996) documents that total yield by farm households in Burkina Faso could be improved by relocating inputs from male-cultivated plots to female-cultivated plots.[3] Schaner (2015) provides evidence indicating that households in Kenya make sub-optimal saving decisions as a result of differences in discount rates of couples. More recent studies (Alem et al. 2017; Miller et al. 2013) show that improved cookstoves, which enhance the quality of life of all household members, are valued at significantly higher levels by women than men, but could not be adopted optimally because women have low decision-making power (autonomy).

Drawing on these studies, we test the hypothesis that female social networks are less effective in promoting technology adoption. If female members of a household have less bargaining power than male members, then female social networks, compared to male social networks, are channels of information transmission that focus on a less-influential decision-maker. Because the female member who learns information through her social network

[3] A related study, Robinson (2012), documents that the response in private consumption to an exogenous shock is significantly different between wives and husbands in western Kenya, implying that informal risk-sharing mechanisms within households are not Pareto-efficient.

lacks the autonomy to make the purchase, we expect the information to be less relevant than in the case of male social networks. Thus, when either passive learning or incentivized communication occurs through female networks, women's lack of decision-making power impedes learning by the relevant decision-maker, and thus the effect of the treatment on WTP in the household should be of lesser magnitude.

Hypothesis 3. *Learning through male social networks increases willingness to pay by a greater amount than learning through female social networks.*

2.4 Experimental Design

To test our hypotheses, we conducted a WTP experiment in 200 unelectrified habitations of Gonda district in the state of Uttar Pradesh, India.[4] Habitations (also called sub-villages or hamlets) are the lowest administrative units in India. The subjects were given an opportunity to purchase a solar lantern in a BDM game. We compared the effects of a network treatment and a communication treatment using randomly assigned male and female contacts. The experiment was conducted in two rounds between the end of July and the beginning of October 2015. The study area was chosen because it had a low electricity access rate, with many unelectrified habitations close to Gonda City, the district capital. To avoid data mining and bias from multiple comparisons, a detailed pre-analysis plan (PAP) listing all research hypotheses and our key empirical specifications was registered with Evidence in the Governance and Politics website.[5]

The primary specification equation can be written as follows:

$$WTP_{ij} = \alpha + \beta_1 N_i + \beta_2 N_i F_i + \gamma_1 N_i C_i + \gamma_2 N_i C_i F_i + \mu_j + \epsilon_{ij}, \qquad (2.1)$$

[4]Before implementation, the experiment was reviewed and approved by the internal review board (IRB) of Columbia University.

[5]The PAP is publicly available at `http://egap.org/registration/1420`.

where WTP_i is the willingness to pay for a solar lantern by household i within habitation j; N_i is a dummy variable coding for whether household i knows a lantern user through its social network (either through the social network of the head or that of the spouse); F_i is a dummy variable coding for whether the lantern user is known through the social network of the female spouse; C_i is a dummy variable coding for whether the household engaged in active communication with the lantern user of his network; μ_j is a vector of habitation fixed effects ($N = 200$); ϵ_{ij} is a random error term. Our objective is to estimate $\beta_1, \beta_2, \gamma_1, \gamma_2$. Throughout, we cluster standard errors by habitations. In this empirical framework, the hypotheses can be expressed as follows. Hypothesis 1 is equivalent to $\beta_1 > 0$ and $\beta_1 + \beta_2 > 0$; Hypothesis 2 to $\gamma_1 > 0$ and $\gamma_1 + \gamma_2 > 0$; Hypothesis 3 to $\beta_2 < 0$ and $\gamma_2 < 0$.

Outcome Variable

In the experiment, subjects were given the opportunity to purchase a solar lantern. Photos of the lantern can be found in the appendix. At the time of the experiment, the retail price of the lantern was 1,200 rupees (USD 18.5). The product features included a 3-watt solar panel, a 6V 4.5Ah battery, a 3-watt, 24-piece surface-mounted-device LED, and a mobile charging socket. We chose the product based on a review of solar lanterns available among Uttar Pradesh distributors. We confirmed the performance of the lanterns - in terms of the quality and duration of the lighting, and the charging power - by using them with the survey team for about a week.

The outcome variable is the subject's WTP measured in the BDM game. As Becker et al. (1964) show, the BDM game recovers the subject's true preference by removing incentives to misrepresent WTP for strategic reasons. In the game, the subject is requested to provide his or her highest WTP for an item, and the price of the item is then drawn from a random distribution. If the price is below the stated WTP, the subject pays the *randomly drawn price*, not the stated WTP. Therefore, the subject has no incentive to understate WTP to obtain a better bargain. This method has been widely applied in development economics to measure WTP (e.g., Guiteras et al. 2013; Hoffmann 2009; Levine et al. 2012) because it is incentive-compatible and provides a continuous demand curve, as opposed to demand estimates for a discrete number of price points (as is the case in a typical randomized-price WTP measurement).

The game was played in the field as follows. Each household is requested to announce their maximal willingness to pay on a 0-1,200 rupee scale, and the actual price is determined by a random draw from a bag which contains 21 balls, each one of them with a number written on it. The number goes from 0 to 1,200 rupees in increments of 100 rupees. The respondent first makes a bid and then randomly draws a ball. If the price on the ball the respondent draws is higher than the bid, the respondent is not allowed to purchase the lantern. If the price on the ball is lower than the bid, the respondent must purchase the lantern at the price that was drawn. As a result, when the respondent makes a bid, he must make sure he has access to the funds. The respondent has only one chance to play, and he cannot change his bid after drawing a ball. Before the respondent played for 'real', the game was played with a bar of soap to make sure the respondent fully understood the rules.

Figure 2.1 displays the distribution of the bids: we see that most subjects made a positive bid, but no subject offered the non-subsidized market price of the lantern. We also note that the willingness to pay displays important variation across individuals, spanning from 0 to 1200, with mean 239 and standard deviation 266.

In measuring WTP, we paid particular attention to training the enumerators so that they explained the procedure to the subjects carefully enough and always conducted the practice round with soap. Based on our observation of the WTP measurement, the subjects understood the rules of the game. No subject complained afterwards or refused to pay in case she or he won the solar lantern. The subjects were sometimes disappointed if they did not win the lantern, but in that case they also did not have to give any money.

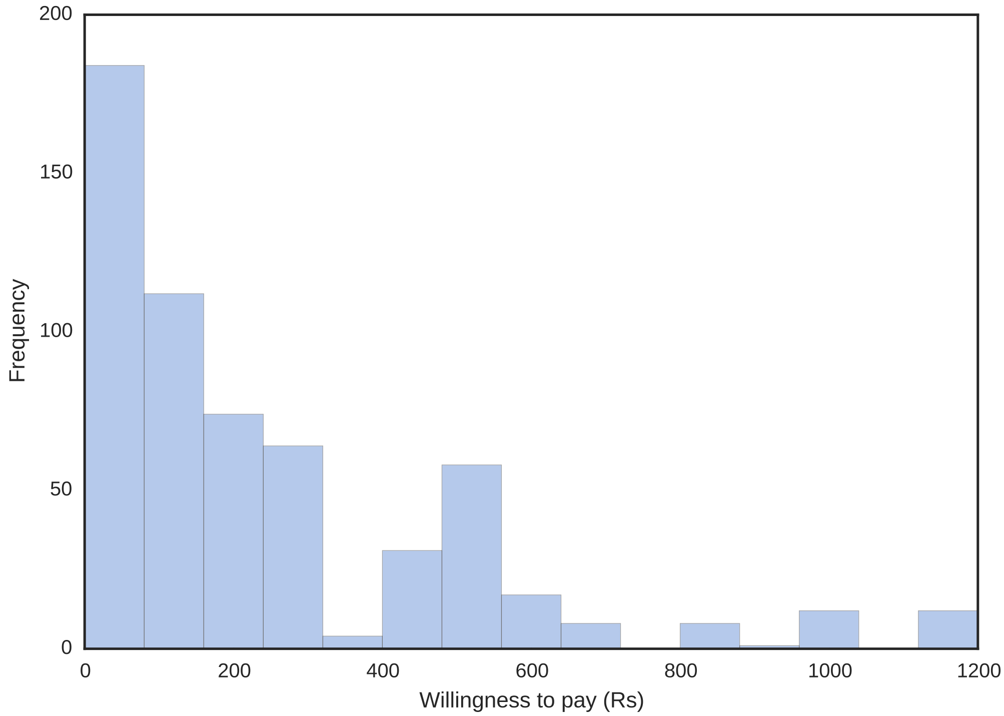


Figure 2.1: Histogram of bids for the solar lantern.

Note: Summary statistics are as follows: minimum = 0; maximum = 1200; mean = 239; standard deviation = 266.

Sampling and Treatments

The data collection began with a mapping of 200 primary habitations and 25 replacement habitations around Gonda City. The enumerators approached the habitations in expanding circles, with habitations near Gonda City visited first and those further away visited later. If a habitation was excluded because of safety concerns or because it had access to grid electricity, a randomly drawn replacement habitation was used instead. Overall, we had to exclude and replace five habitations. The map of the study area and habitations is shown in Figure 2.2.

Within each habitation, the enumerators approached a randomly chosen "seed" household and, depending on the treatment, interviewed either an adult male or female member. The seed was requested to provide names of three friends with whom he or she interacts on

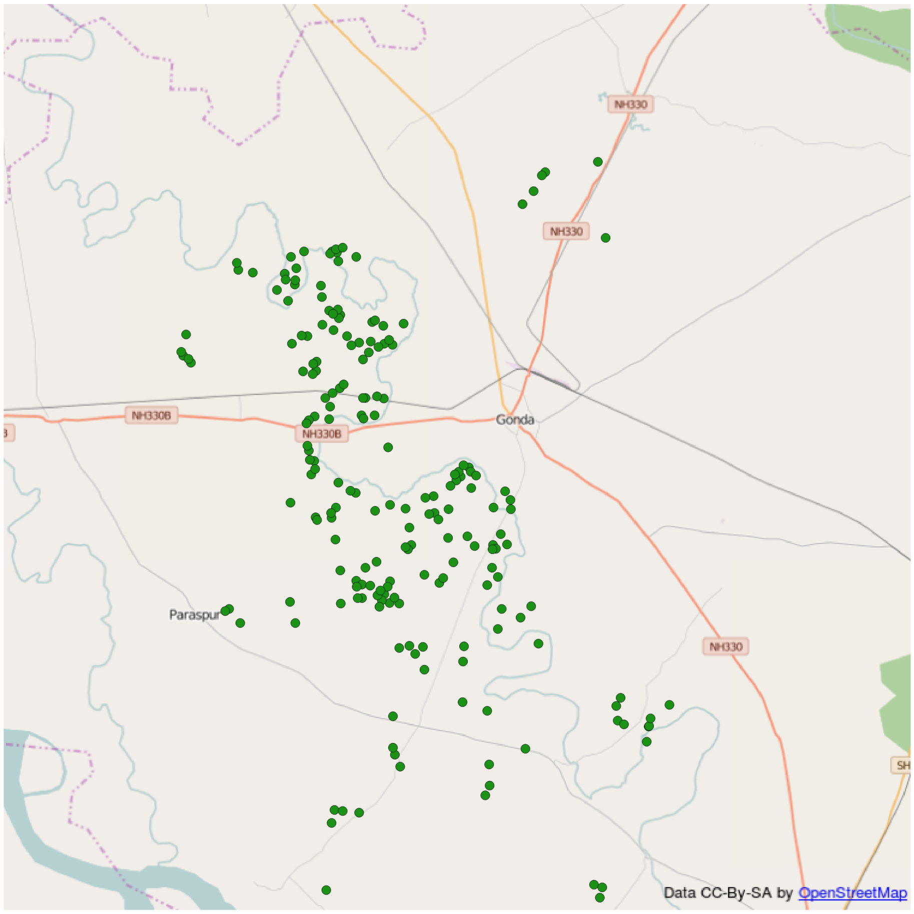


Figure 2.2: Map of study area around Gonda City.

Note: The green dots indicate the study habitations.

a regular basis, and the three friends were then randomly assigned to three groups: control, network, and communication. The control group was interviewed on the same day and the network and communication groups approximately 30 days after the initial interview. If the chosen friend was not the household head, we interviewed the head of the household to which that friend belongs. Households in the three groups were offered the possibility of buying a solar lantern through a BDM game.

The timeline of the experiment is summarized in Figure 2.3. The experiment began with sampling and the interviews of the control group in July-August 2015. In each habitation, the network and communication groups were interviewed approximately one month after

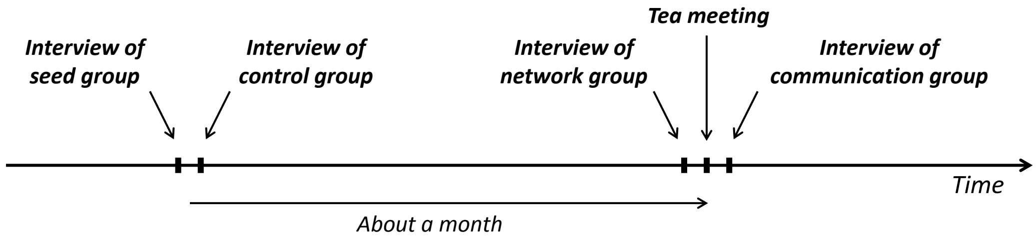


Figure 2.3: Timeline of the experiment.

sampling. We surveyed the network group at the same time as the communication group to avoid treatment spillovers. Table 2.1 summarizes the size of the different treatment groups. We visited a total of 197 habitations, 98 assigned to the male seed treatment and 99 to the female seed treatment. Three habitations were dropped because the network and communications friends were no longer living in the surroundings, and hence could not be surveyed.

The male-female treatment was randomized at the habitation level. One of the researchers drew a random number for each habitation and assigned the highest 100 numbers to the female treatment. All seed households were given a free solar lantern in exchange for taking part in the survey. They were also paid 100 rupees conditional on inviting one of the three friends for a tea meeting to introduce the solar lanterns and discuss their user experience. Our survey team, consisting of enumerators who speak the local dialect, attended all tea meetings. They specifically told the seed households that their goal was not to convince their friend to buy a lantern but only to share stories about their experience and the performance of the lanterns.

Within each habitation, the three friends named by the seed were randomly assigned to the control or to the network or communication treatment. The household of the friend in the control group was visited and asked for WTP immediately after the seed household provided the name of three friends. The procedure for the households of those in the network and communication groups was similar, except for the two following differences. First, the

Table 2.1: Size of treatment groups.

	Total number of habitations		
	Control	**Network**	**Communication**
Male Seed	98	98	98
Female Seed	99	99	99

Note: In all treatments, the sample household's head is interviewed. The gender treatment is randomized across habitations; the information treatment is randomized within habitations.

visit to the network and communication households took place about a month later. A one-month lag is a way to ensure that knowledge about the lantern can naturally diffuse from the seed household to peer households. Second, before playing the BDM game with the communication household, the seed invited his/her communication friend over to discuss his/her experience of the lantern.

Covariate Balance and Power Analysis

The balance table for the information treatment is shown in Table 2.2. As the table shows, the treatment groups are balanced across most covariates, with a few exceptions: gender of the respondent, savings and indebtedness. The control group has significantly more female heads of household and about 450 rupees less in savings compared to the network and communication groups. This is a potential source for concern given households with more savings would be in a better position to bid higher prices. For this reason, as a robustness check, we include these variables in additional regression analysis.

The balance table across the seed gender treatments is shown in Table 2.3. As could be expected, within each information treatment group the households referred by the female seeds are more likely to be headed by a female, while the households referred by the male seeds are usually headed by a male. It follows that the different groups display significant differences for variables such as education, consumption expenses or literacy.

Standard power analysis shows that the experiment can identify plausible treatment effects. Using the control group's mean and standard deviation (134 and 181 respectively),

Table 2.2: Balance table across treatments and associated t-tests.

	Cont	Net	DIFF	Cont	Comm	DIFF	Net	Comm	DIFF
1) Individual:									
Female respondent	0.355	0.198	0.157***	0.355	0.254	0.102**	0.198	0.254	-0.0558
	(0.480)	(0.399)	(3.54)	(0.480)	(0.436)	(2.20)	(0.399)	(0.436)	(-1.32)
Year of birth	1972.1	1971.8	0.239	1972.1	1970.7	1.345	1971.8	1970.7	1.107
	(14.76)	(14.24)	(0.16)	(14.76)	(12.91)	(0.96)	(14.24)	(12.91)	(0.81)
Education	1.944	2.041	-0.0964	1.944	1.893	0.0508	2.041	1.893	0.147
	(1.352)	(1.435)	(-0.69)	(1.352)	(1.255)	(0.39)	(1.435)	(1.255)	(1.08)
Reads Hindi	0.477	0.487	-0.0102	0.477	0.482	-0.00508	0.487	0.482	0.00508
	(0.501)	(0.501)	(-0.20)	(0.501)	(0.501)	(-0.10)	(0.501)	(0.501)	(0.10)
2) Household:									
Number of children	3.693	3.918	-0.225	3.693	4.015	-0.323	3.918	4.015	-0.0979
	(2.106)	(2.032)	(-1.07)	(2.106)	(2.085)	(-1.51)	(2.032)	(2.085)	(-0.47)
Number of children in school	1.370	1.412	-0.0426	1.370	1.649	-0.280*	1.412	1.649	-0.237
	(1.550)	(1.562)	(-0.27)	(1.550)	(1.657)	(-1.71)	(1.562)	(1.657)	(-1.45)
Household size	7.310	7.183	0.127	7.310	7.289	0.0203	7.183	7.289	-0.107
	(3.916)	(3.379)	(0.34)	(3.916)	(3.375)	(0.06)	(3.379)	(3.375)	(-0.31)
3) Wealth:									
Monthly Expenses	4176.6	4376.6	-200	4176.6	4530.5	-353.8	4376.6	4530.5	-153.8
	(2334.3)	(3412.5)	(-0.68)	(2334.3)	(2810.7)	(-1.36)	(3412.5)	(2810.7)	(-0.49)
Amount of Savings	223.4	682.2	-458.9***	223.4	661.4	-438.1***	682.2	661.4	20.81
	(673.8)	(884.1)	(-5.79)	(673.8)	(1038.3)	(-4.97)	(884.1)	(1038.3)	(0.21)
In debt	0.467	0.609	-0.142***	0.467	0.477	-0.0102	0.609	0.477	0.132***
	(0.500)	(0.489)	(-2.85)	(0.500)	(0.501)	(-0.20)	(0.489)	(0.501)	(2.65)
Owns a business	0.0355	0.0660	-0.0305	0.0355	0.0711	-0.0355	0.0660	0.0711	-0.00508
	(0.186)	(0.249)	(-1.38)	(0.186)	(0.258)	(-1.57)	(0.249)	(0.258)	(-0.20)
Amount of land (acres)	1.310	1.443	-0.134	1.310	1.415	-0.106	1.443	1.415	0.0278
	(1.888)	(1.936)	(-0.69)	(1.888)	(1.426)	(-0.63)	(1.936)	(1.426)	(0.16)
Owns cattle	0.873	0.873	0	0.873	0.929	-0.0558*	0.873	0.929	-0.0558*
	(0.334)	(0.334)	(0.00)	(0.334)	(0.258)	(-1.86)	(0.334)	(0.258)	(-1.86)
Owns a phone	0.853	0.838	0.0152	0.853	0.868	-0.0152	0.838	0.868	-0.0305
	(0.355)	(0.370)	(0.42)	(0.355)	(0.339)	(-0.44)	(0.370)	(0.339)	(-0.85)
4) Lighting:									
Number of kerosene lamps	2.376	2.421	-0.0457	2.376	2.401	-0.0254	2.421	2.401	0.0203
	(1.266)	(1.229)	(-0.36)	(1.266)	(1.043)	(-0.22)	(1.229)	(1.043)	(0.18)
Hours of lighting	5.178	4.782	0.396*	5.178	5.033	0.145	4.782	5.033	-0.251
	(2.368)	(1.814)	(1.86)	(2.368)	(1.766)	(0.69)	(1.814)	(1.766)	(-1.39)

t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: A rank-sum test (Wilcoxon-Mann-Whitney) was also performed for the variables that do not approximate a normal distribution. The only difference with the t-tests are as follows: 1) The difference between control and communication for the number of children that go to school is significant at the 10% level, 2) The difference between network and communication for hours of lighting is now significant at the 10% level.

Table 2.3: Balance table across treatments and seed gender and associated t-tests.

	Cont M	Cont F	DIFF	Net M	Net F	DIFF	Comm M	Comm F	DIFF
1) Individual:									
Female respondent	0.153	0.556	-0.402***	0.102	0.293	-0.191***	0.153	0.354	-0.200***
	(0.362)	(0.499)	(-6.47)	(0.304)	(0.457)	(-3.45)	(0.362)	(0.480)	(-3.31)
Year of birth	1971.3	1972.8	1.532	1971.6	1972.1	-0.529	1969.7	1971.8	-2.043
	(15.89)	(13.58)	(-0.73)	(15.06)	(13.44)	(-0.26)	(12.82)	(12.97)	(-1.11)
Education	2.051	1.838	.213	2.265	1.818	0.447**	1.980	1.808	0.172
	(1.357)	(1.345)	(1.10)	(1.544)	(1.289)	(2.21)	(1.284)	(1.226)	(0.96)
Reads Hindi	0.541	0.414	0.127*	0.592	0.384	0.208***	0.490	0.475	0.0150
	(0.501)	(0.495)	(1.79)	(0.494)	(0.489)	(2.97)	(0.502)	(0.502)	(0.21)
2) Household:									
Number of children	3.543	3.837	-0.294	3.823	4.010	-0.187	3.918	4.113	-0.196
	(2.077)	(2.133)	(-0.97)	(2.026)	(2.043)	(-0.64)	(2.045)	(2.131)	(-0.65)
Number of children in school	1.223	1.510	-0.287	1.417	1.408	0.00850	1.526	1.773	-0.247
	(1.489)	(1.601)	(-1.28)	(1.499)	(1.630)	(0.04)	(1.690)	(1.623)	(-1.04)
Household size	7.357	7.263	0.0945	7.765	6.606	1.159**	7.939	6.646	1.292***
	(3.946)	(3.906)	(0.17)	(3.705)	(2.927)	(2.44)	(3.472)	(3.163)	(2.73)
3) Wealth:									
Monthly Expenses	3899.0	4451.5	-552.5*	4844.9	3913.1	931.8*	4940.8	4124.2	816.6**
	(2240.9)	(2403.0)	(-1.67)	(4403.4)	(1913.7)	(1.93)	(3206.4)	(2299.6)	(2.06)
Amount of Savings	278.6	168.7	109.9	717.3	647.5	69.87	672.4	650.5	21.94
	(776.2)	(552.7)	(1.15)	(914.5)	(856.1)	(0.55)	(740.3)	(1270.3)	(0.15)
In debt	0.480	0.455	0.0250	0.582	0.636	-0.0547	0.480	0.475	0.00484
	(0.502)	(0.500)	(0.35)	(0.496)	(0.483)	(-0.78)	(0.502)	(0.502)	(0.07)
Owns a business	0.0510	0.0202	0.0308	0.0816	0.0505	0.0311	0.0612	0.0808	-0.0196
	(0.221)	(0.141)	(1.17)	(0.275)	(0.220)	(0.88)	(0.241)	(0.274)	(-0.53)
Amount of land (acres)	1.196	1.422	-0.226	1.431	1.455	-0.0248	1.604	1.228	0.375*
	(1.157)	(2.404)	(-0.84)	(1.678)	(2.170)	(-0.09)	(1.638)	(1.158)	(1.86)
Owns cattle	0.827	0.919	-0.0927*	0.867	0.879	-0.0114	0.918	0.939	-0.0210
	(0.381)	(0.274)	(-1.96)	(0.341)	(0.328)	(-0.24)	(0.275)	(0.240)	(-0.57)
Owns a phone	0.816	0.889	-0.0726	0.806	0.869	-0.0626	0.908	0.828	0.0799*
	(0.389)	(0.316)	(-1.44)	(0.397)	(0.339)	(-1.19)	(0.290)	(0.379)	(1.66)
4) Lighting:									
Number of kerosene lamps	2.235	2.515	-0.280	2.439	2.404	0.0347	2.541	2.263	0.278*
	(1.250)	(1.273)	(-1.56)	(1.332)	(1.124)	(0.20)	(1.141)	(0.921)	(1.88)
Hours of lighting	5.082	5.273	-0.191	4.806	4.758	0.0485	5.005	5.061	-0.0555
	(2.218)	(2.515)	(-0.57)	(1.892)	(1.743)	(0.19)	(1.709)	(1.828)	(-0.22)

t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: A rank-sum test (Wilcoxon-Mann-Whitney) was also performed for the variables that do not approximate a normal distribution. The only difference with the t tests are as follows: 1) The difference in education level is significant at 10% in the control group, 2) The difference in household expenses is not significant in the network group, 3) The difference in savings of the seeds is significant at 10% in the communication group, 4) The difference in irrigated land is not significant in the communication group, 5) The difference in the number of kerosene lamps is not significant in the communication group.

a standard deviation's uniform increase (to 315, with a standard deviation of 362) would be detected with an $\alpha = 0.95$ probability if the control and treatment group each had at least 65 participants. In our setting, each group has 200 subjects, and, we cluster standard errors at the habitation level ($N = 200$). We also control for habitation fixed effects, which enables us to estimate the treatment effects more precisely.

2.5 Results

Main Estimates

Figure 2.4 shows the distribution of bids across treatment groups. There is a noticeable change in the distribution between the control group and the network group, and between the network group and the communication group: the distribution becomes flatter and displays a much fatter left tail. This likely indicates that our treatments have positive effects on WTP. We hardly notice important differences, however, when comparing the distribution across gender of the seed; this indicates that our gender treatment is not likely to have any effect.

We display box plots of WTP for the different treatment groups in Figure 2.5. We also show the value of the mean WTP across treatments in Table 2.4. Formal test results on whether or not the differences between these various means are significant are reported in Table 2.5 and Table 2.6[6]. We find that the mean WTP in the network and communication treatments is significantly higher than in the control. Table 2.5 reveals that there is also a significant difference between the network and communication treatments when the sample is not split by gender. However, when looking only at the sample with female seeds, there is no significant difference between the means of the network and communication treatments. Finally, box plots on Figure 2.5 seem to indicate that there is a difference between Male and Female in the control group, but less so in the treatment groups. This is confirmed in Table

[6]We performed both t-tests and rank-sum tests.

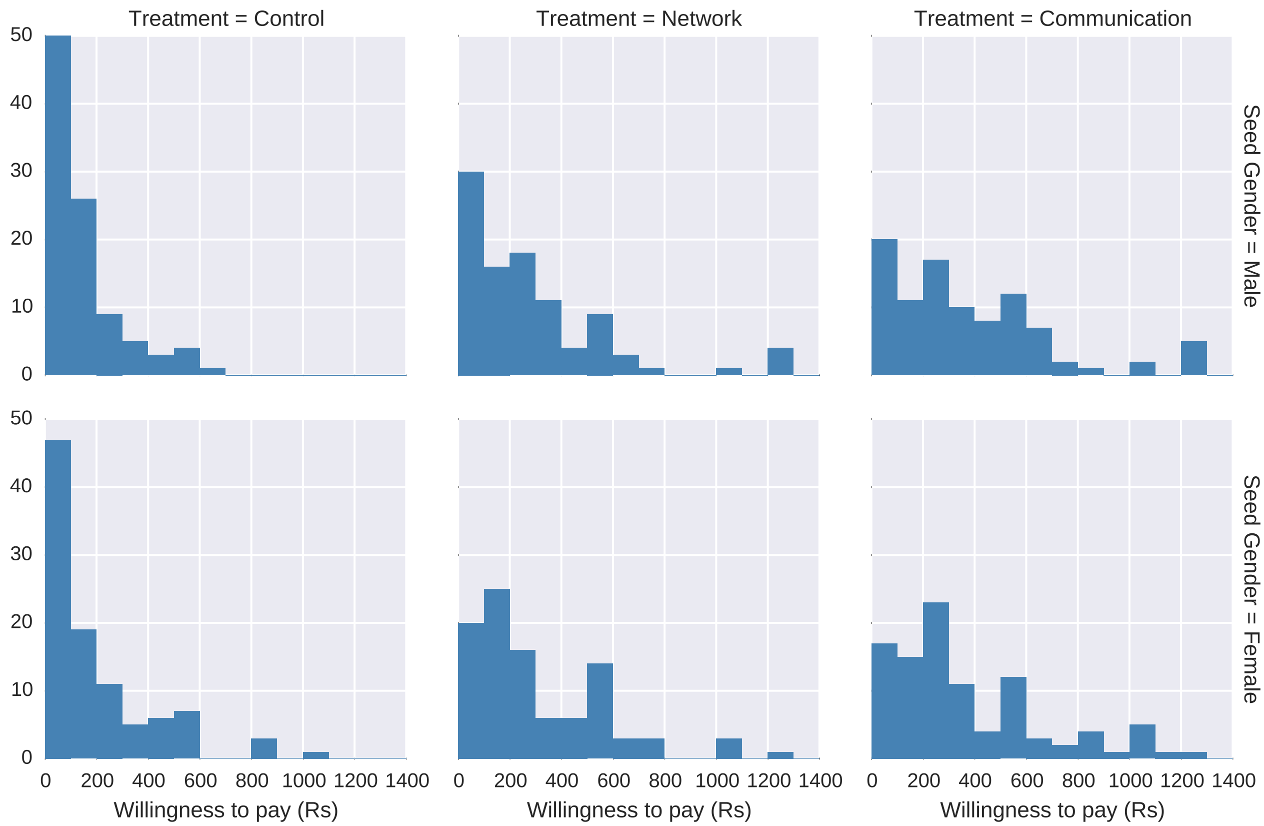


Figure 2.4: Faceted histogram of bids for the solar lantern.

Table 2.4: Means across treatments.

	Control	Network	Communication
WTP - All seeds	133.5	254.9	330.2
	(180.6)	(267.0)	(300.4)
WTP - Male Seed	107.1	245.4	334.2
	(141.6)	(278.9)	(308.1)
WTP - Female Seed	159.6	264.4	326.3
	(209.8)	(255.8)	(294.5)

Variable: Willingness to Pay. Means and standard deviations.

2.6: the difference in the control group is significant at the 5%. However, we note that the difference is not significant any longer when using the rank-sum test.

Mean comparisons, however, do not control for unobserved heterogeneity across habitations and for correlation between observations within the same habitation. We therefore proceed to using regression analysis with fixed effects and clustered standard errors at the

Table 2.5: Tests for means across treatments.

	Differences		
	Control - Network	Control - Communication	Network - Communication
WTP - All seeds	-121.4***	-196.7***	-75.26***
	(-5.27)	(-7.86)	(-2.61)
WTP - Male Seed	-138.2***	-227.1***	-88.85**
	(-4.37)	(-6.61)	(-2.10)
WTP - Female Seed	-104.8***	-166.7***	-61.83
	(-3.14)	(-4.59)	(-1.57)

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Chi-square tests for whether the mean WTP is the same in all treatment groups always yield that the three coefficients are different at the 1% level in the whole sample as well as in the subsample of female seeds and the subsample of male seeds. Rank-sum tests were also performed for each of the t-tests and p-values were found identical. The χ^2 test statistic for identical mean WTP across treatment groups is 94.17; with 34 degrees of freedom, the associated p-value equals 0. The χ^2 test statistic for the WTP to be equal in all treatment groups within the subsample of male seed is 60.99; with 30 degrees of freedom, the associated p-value equals 0.001. The χ^2 test statistic for the WTP to be equal in all treatment groups within the subsample of female seed is 55.69; with 32 degrees of freedom, the associated p-value equals 0.006. The z statistics for the rank-sum tests are as follows. First row: -5.5; -7.9; -2.8. Second row: -4.2; -6.2; -2.4. Third row: -3.6; -5.0; -1.5.

Table 2.6: Tests for means across seed gender.

	Differences
	Male - Female
WTP - Control	-52.45**
	(-2.05)
WTP - Network	-19.07
	(-0.50)
WTP - Communication	7.948
	(0.18)

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Rank-sum tests are as follows. Control group: z = -1.463, Prob ¿ —z— = 0.1435. Network: z =-0.876, Prob ¿ —z— = 0.3811. Communication: z = 0.166, Prob ¿ —z— = 0.8682.

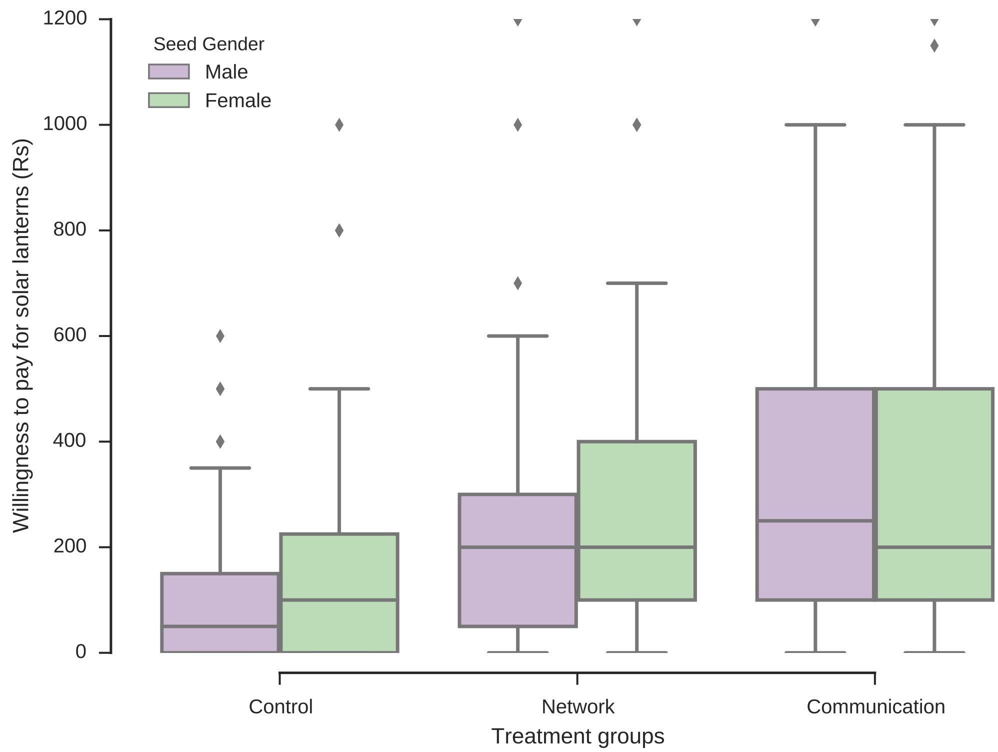


Figure 2.5: Boxplots of bids for the solar lantern.

habitation level. The main results from regression analysis are shown in Table 2.7. In all regressions, the standard errors are clustered at the habitation level. Habitation fixed effects are not included in the second column because the gender treatment was randomized across habitations. Results show that the network treatment increased WTP by almost 120 Rupees compared to the control group. Given the mean WTP of the control group was 134 Rupees,[7] this corresponds to a 90% increase. Furthermore, compared to the control group, the communication treatment increased WTP by 195 Rupees which corresponds to a 145% increase. The gender treatment, however, does not appear to have a statistically significant effect. The inclusion of habitation fixed effects in column 4 further reduces the coefficient for the interaction of the gender treatment with the information treatment in the negative values.

[7]Similarly, the value of the intercept in model 1 of Table 2.7 is 134.5 Rupees.

Table 2.7: Main results for experimental treatments.

	(1) WTP	(2) WTP	(3) WTP	(4) WTP
Network	119.883***		116.383***	136.988***
	(22.115)		(30.297)	(30.847)
Communication	195.078***		204.785***	224.416***
	(22.925)		(32.325)	(32.086)
Seed Gender		22.241		
		(24.674)		
Network x Female Seed			9.080	-34.067
			(38.292)	(44.229)
Communication x Female Seed			-16.890	-57.749
			(42.631)	(45.745)
Habitation fixed effects	Yes	No	No	Yes
Clustered SE	Yes	Yes	Yes	Yes
R-squared	0.157	0.002		0.161
Observations	585	585	585	585

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: In column 1, the coefficients for Network and Communication are different at the 1% level.

Robustness Checks

In Table 2.8, we include controls for monthly savings, one of the imbalanced covariates. We see that the treatment effects coefficients slightly decrease from 120 to 108 Rupees in the network group and from 195 to 184 Rupees in the communication group. Yet, the effects remain robust. The coefficient for monthly savings is significant at the 5% level but the magnitude is small: every additional Rupee in savings correlates with a WTP increase of 0.026 Rupees. Given the imbalance of savings across treatment groups, this represents an average contribution to the WTP of about 6 Rupees in the control group and 17 to 18 Rupees in the network and communication groups. The contribution of savings to the WTP is therefore an order of magnitude lower than the contribution of our information treatments. In fact, the raw correlation coefficient between WTP and savings is only 0.15. This can be visualized on the scatter plot of WTP for the entire sample, with amount of savings shown in the Appendix: those who had the highest amount of savings are not those who bid the highest WTP. In regression 2, we interact monthly savings with the treatment dummies. The coefficient for the interaction term is negative and significant at the 10% level, indicating that savings and WTP correlate even in this treatment group. We also re-run the regression using monthly savings in logs instead of levels and find similar results. Specifically, we note that the estimated treatment effects decreases slightly, from 120 to 103 Rupees in the network group and from 195 to 177 Rupees in the communication group, but, overall, the effects remain large and significant at the 1% level. Finally, regression 5 estimates the treatment effects for the sub-sample of respondents who declared having zero savings. This regression therefore includes only about half of the observations. We see that the treatment effects found within this subsample are very similar to those found for the whole sample. This confirms that monthly savings are not the main driver of our treatment effects.

In Table 2.9, we add other control variables. In column 1, we control for whether the household head is female because this was the other unbalanced variable. Treatment effects for both the network and communication groups change little. In column 2, we control for both whether the household head is female and for the amount of monthly savings. The main treatment effects are slightly reduced but remain large and significant at the 1% level. In column 3, we control for the date when the household was surveyed. Harvesting of maize and rice in the study area started at the end of September and early October respectively. This timing partly coincided with our survey of the network and communication groups: about 20% of our treated households were interviewed after September 25[8]. If those sampled households began selling their harvest, they would likely have been able to afford greater

[8] Rice Knowledge Management Portal, maintained by the Indian Council of Agricultural Research (http://www.rkmp.co.in/content/rice-growing-seasons-of-uttar-pradesh) indicates that in Uttar Pradesh summer rice is harvested in April-May and Kharif rice in November-December. On the other hand, wheat is harvested around March-April in the eastern part of Uttar Pradesh, and around mid-April in the western part (see http://www.archive.india.gov.in/citizen/agriculture/index.php?id=11). Our local team, however, indicated that a reasonable estimate for the first day of harvest in the region around Gonda City was September 25 for Maize and October 5 for rice, and we use these more conservative dates for our robustness check.

Table 2.8: Main results for experimental treatments controlling for amount of savings.

	(1)	(2)	(3)	(4)	(5)
Network	107.560***	114.829***	103.161***	119.744***	117.944***
	(22.727)	(28.718)	(25.966)	(33.841)	(36.070)
Communication	183.525***	201.240***	177.301***	229.662***	214.382***
	(23.902)	(25.510)	(27.383)	(39.679)	(43.535)
Amount of Savings	0.026**	0.066**			
	(0.013)	(0.033)			
Network x Savings		-0.037			
		(0.039)			
Communication x Savings		-0.053*			
		(0.031)			
Savings (log)			5.689	19.353**	
			(4.340)	(7.478)	
Network x log Savings				-14.007	
				(8.860)	
Communication x log Savings				-22.412**	
				(9.470)	
Habitation fixed effects	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes
R-squared	0.165	0.170	0.162	0.173	0.180
Observations	585	585	585	585	315

Standard errors in parentheses
Model57 is for the sub-sample of respondents that declare zero savings.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: We also tested a specification with logarithmic savings, but the coefficient on savings was found insignificant (p-value=0.19).

expenditures, and consequently have a higher WTP for the solar lanterns. We therefore investigate the robustness of our treatment effect to this possible "wealth effect".

In order to investigate the possible role of a wealth effect, we control in our regression for the date of interview. Specifically, the variable "Date" is the month and day of the month on which the respondent was interviewed. If there is a wealth effect due to the sale of crops, respondents interviewed toward the end of the experiment are more likely to have access to cash and bid a higher price. The coefficient on 'Date' then should be positive. Results show that the coefficient is not significant and leans toward negative values.[9] This shows

[9]Standard errors and coefficients are very large in this case due to the collinearity between our treatment

that respondents interviewed last were no more likely to bid higher amounts, which provides supporting evidence against a wealth effect from the harvest season. In column 4, our main results remain robust to the inclusion of seven additional control variables. Most variables, such as the level of education, expenditures, whether or not the respondent is in debt, and household size, display small and insignificant coefficients. The number of children going to school shows a slightly larger coefficient; the variable is statistically insignificant. Only the number of kerosene lamps displays a coefficient that is significant at the 10% level: households owning many kerosene lamps also bid slightly higher WTP. Intuitively, households with a greater number of kerosene lamps are likely to be households with a greater need for lighting products, which should translate into higher WTP.

Mechanisms

In this section, we investigate the possible mechanisms to explain why our treatments are effective. Table 2.10 displays the mean response to various survey questions for each treatment group. The exact phrasing of the questions can be found in the appendix. We note that, compared to the control group, respondents in the network and communication groups are much more likely to have seen a solar lantern before and they are much more likely to know someone who owns a lantern. This is fully consistent with our experimental design and provides evidence that our treatments were properly implemented. Furthermore, close to 90% of the respondents in the network and communication group stated that they had conversations with that person more than three times a week. Hence, the major factor explaining the difference between the network and the communication groups is unlikely to be the level of interactions with a friend who owns a solar lantern. The third and fourth variables in the table provide some insights as to why WTP has increased. Contrary to the control group, most people in the network and communication groups now believe that, to function properly, a solar lantern needs proper maintenance. They also estimate the cost of

dummies and the date variable.

Table 2.9: Main results for experimental treatments with control variables included.

	(1)	(2)	(3)	(4)
Network	115.107***	103.683***	388.290**	107.520***
	(22.469)	(22.937)	(180.316)	(23.925)
Communication	191.915***	181.072***	470.514***	180.476***
	(23.112)	(24.064)	(180.690)	(25.348)
Female Head	-31.046	-27.911	-29.942	-23.510
	(27.096)	(26.594)	(26.485)	(29.275)
Amount of Savings		0.026**	0.027**	0.025**
		(0.013)	(0.013)	(0.012)
Interview date			-7.698	
			(4.800)	
Education				4.459
				(11.716)
Monthly Expenses				-0.005
				(0.005)
In debt				-26.115
				(26.128)
Household size				-2.565
				(3.855)
Number of children to school				11.893
				(7.433)
Number of kerosene lamps				19.780*
				(11.547)
Hours of lighting				1.415
				(6.504)
Habitation fixed effects	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes
R-squared	0.160	0.167	0.176	0.181
Observations	585	585	584	574

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.10: Summary statistics for some key solar lantern related variables highlighting possible mechanisms.

	Cont.	Net.	DIFF	Cont.	Comm.	DIFF	Net.	Comm.	DIFF
Seen lantern before	0.244	0.934	-0.690***	0.244	0.949	-0.706***	0.934	0.949	-0.0152
	(0.430)	(0.249)	(-19.49)	(0.430)	(0.220)	(-20.49)	(0.249)	(0.220)	(-0.64)
Know someone with lantern	0.132	0.924	-0.792***	0.132	0.944	-0.812***	0.924	0.944	-0.0203
	(0.339)	(0.266)	(-25.78)	(0.339)	(0.230)	(-27.80)	(0.266)	(0.230)	(-0.81)
Can function properly	0.533	0.0508	0.482***	0.533	0.0914	0.442***	0.0508	0.0914	-0.0406
	(0.500)	(0.220)	(12.39)	(0.500)	(0.289)	(10.73)	(0.220)	(0.289)	(-1.57)
Cost estimate	627.1	838.7	-211.6***	627.1	736.6	-109.5**	838.7	736.6	102.1*
	(558.7)	(647.9)	(-3.47)	(558.7)	(538.9)	(-1.98)	(647.9)	(538.9)	(1.70)
Innovative product	4.939	4.980	-0.0405	4.939	4.970	-0.0305	4.980	4.970	0.0100
	(0.373)	(0.226)	(-1.30)	(0.373)	(0.200)	(-1.01)	(0.226)	(0.200)	(0.47)
Superior to kerosene lamps	4.995	4.980	0.0152	4.995	4.985	0.0101	4.980	4.985	-0.00508
	(0.0714)	(0.174)	(1.13)	(0.0714)	(0.123)	(1.00)	(0.174)	(0.123)	(-0.33)
Will recommend to others	4.995	4.975	0.0203	4.995	4.949	0.0457*	4.975	4.949	0.0254
	(0.0712)	(0.187)	(1.42)	(0.0712)	(0.346)	(1.81)	(0.187)	(0.346)	(0.91)

such a product at a higher level than the control group. This indicates that a key lesson learned from their friend's experience relates to the technical quality of the lantern. At first, villagers might expect that solar lanterns are nothing more sophisticated than kerosene lanterns. They then observe their friend taking care of it; they note the photovoltaic panel that is connected to the lamp, which allows the battery to be charged. As a result, they perceive the product as a sophisticated item that requires careful maintenance and are therefore willing to pay a higher price. Interestingly, we note that respondents perceive solar lanterns positively. Almost everyone answered "Definitely" to the questions of whether the lantern was innovative, whether it was superior to a kerosene lamp, and whether they would recommend it to a friend over a kerosene lamp. This is despite the fact that most of those in the control group confirm they had never seen a solar lantern before and did not know anybody who owned one. It is also despite the fact that most people in the treated groups now recognize that a solar lantern can not function without proper maintenance.

In one of the survey questions, we asked respondents how much they thought the lantern

Table 2.11: Results with cost estimate of solar lanterns as dependent variable.

	(1) Estimated cost	(2) Estimated cost
WTP	0.390***	
	(0.091)	
Network		211.589***
		(53.725)
Communication		109.538**
		(53.985)
Habitation fixed effects	No	Yes
Clustered SE	Yes	Yes
R-squared	0.031	0.036
Observations	585	591

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

cost. The mean estimate approximates 730 Rupees with a standard deviation of about 500. Interestingly, the correlation between cost estimates and the willingness to pay is small in magnitude. Regression 1 in Table 2.11 shows that every 100 extra Rupees in cost estimate correlates with an increase in willingness to pay of only about 8 Rupees. In column 2 of the same table, we investigate the treatment effects on the estimated cost. We note that both the network and communication groups display higher estimated costs compared to the control group. In particular, respondents in the network group estimated the lantern at a higher cost than did respondents in the communication group. Yet, they bid lower prices in the BDM game on average. This indicates that the main mechanism through which the tea meetings affect willingness to pay is not through increasing respondents' perception of the product's cost. It is rather through improving knowledge about the attributes of the solar lantern technology.

Why Didn't Gender Affect Willingness to Pay?

In order to shed light on why gender did not affect WTP, we present the covariates of the friends chosen by the male and female seeds, including formal statistical tests of differences in Table 2.12. Consistent with existing gender inequalities in India, we observe that female seeds are less likely to be educated and literate. We also note that female seeds have a weaker connection to the village's social life: not only are they less likely to participate in village meetings or religious and political events, but have also somewhat less trust in other villagers, and say that they have fewer friends and spend less time with these friends, compared to male seeds. Notably, they are much more likely to be born outside the village, which might play a role in explaining these findings. One question in the survey asked seeds who they thought would mostly be using the lanterns. It is interesting to see that 70% of female seeds declared that they would be the one using the lantern. Furthermore, 30% of male seeds answered that their spouse would mostly use the product. Hence it appears that both genders agree that the lantern is a product useful to women.

Given these important differences between the two seed groups, we can expect that they choose friends who are different in several characteristics. Table 2.13 reports characteristics of the household heads of the female seeds' friends and the male seeds' friends. We observe that household heads in the female seed group are less likely to be educated and literate, and have fewer savings. But, very importantly, we note that they are also more likely to be female. In other words, female seeds are more likely to choose a friend who is herself the head of her household, and it is likely that the differences in education, literacy and savings follow from that fact.

Our hypothesis about the gender treatment relies on the assumption that a male household head discounts information carried through a female network. Here, the sample of friends named by the female seeds are in fact composed of a greater number of female household heads. These respondents, being female, are less likely to discount information received through their direct social network. As a result, it is possible that the absence of a treatment effect results from such a composition effect. To investigate this further, we test the sensitivity of our results by dividing the sample according to the gender of the household head. Table 2.14 displays summary statistics for the two subsamples. We note that, overall, female household heads are younger, have more children, are less educated and less likely to

Table 2.12: Summary statistics for the two seed groups

	Male Seeds	Female Seeds	Difference
Born in village	0.970	0.140	0.830***
	(0.171)	(0.349)	(11.78)
Number of children	3.714	4.530	-0.816**
	(2.021)	(2.418)	(-2.11)
Education	2.090	1.480	0.610***
	(1.296)	(0.990)	(3.86)
Education of spouse	1.265	2.360	-1.095***
	(0.807)	(1.345)	(-7.10)
Reads Hindi	0.530	0.310	0.220***
	(0.502)	(0.465)	(3.15)
Amount of savings	387	228	159**
	(1197.5)	(1076.1)	(2.18)
Children use lighting for studying	0.560	0.700	-0.140**
	(0.499)	(0.461)	(-2.05)
Current lighting bad	4.175	4.544	-0.369**
	(1.315)	(0.876)	(-1.77)
Mostly be using: myself	0.490	0.700	-0.210***
	(0.502)	(0.461)	(-3.02)
Mostly be using: my spouse	0.300	0.0500	0.250***
	(0.461)	(0.219)	(4.64)
Discuss how to spend money	1.600	-0.180**	
	(0.684)	(0.603)	(-1.96)
Women should work outside	3.690	4.470	-0.780***
	(1.733)	(1.132)	(-3.10)
Participation in village meetings	0.280	0.140	0.140**
	(0.570)	(0.377)	(1.77)
Participation in farmers' cooperative meetings	0.140	0.0200	0.120***
	(0.377)	(0.200)	(3.28)
Participation in religious group events	1.050	0.800	0.250**
	(0.702)	(0.739)	(2.46)
Participation in political events	0.370	0.100	0.270***
	(0.630)	(0.333)	(3.66)
Trust other villagers	3.830	3.280	0.550**
	(1.436)	(1.694)	(2.14)
Spend time with friends (dummy)	0.380	0.240	0.140**
	(0.488)	(0.429)	(2.14)
Number of friends	10.02	6.390	3.630***
	(11.52)	(4.722)	(3.05)

Note: Only variables with significant differences are reported. The corresponding z statistics of the rank-sum test is reported.

Table 2.13: Social network analysi

	Male Seed Friends	Female Seed Friends	Difference
Female respondent	0.136	0.401	-0.265***
	(0.343)	(0.491)	(-7.25)
Education	2.099	1.822	0.277***
	(1.400)	(1.283)	(2.95)
Reads Hindi	0.541	0.424	0.117***
	(0.499)	(0.495)	(2.83)
Amount of savings	556.1	488.9	67.23**
	(834.7)	(964.1)	(2.12)
Household size	7.687	6.838	0.849***
	(3.708)	(3.360)	(2.90)
Can function properly	0.255	0.195	0.0598*
	(0.437)	(0.397)	(1.74)
Would feel safer if more light	4.990	4.959	0.0303*
	(0.130)	(0.270)	(1.90)
Was victim of kerosene fire	0.184	0.108	0.0759***
	(0.388)	(0.311)	(2.62)
Knows a victim of a kerosene fire	0.323	0.249	0.0740**
	(0.468)	(0.433)	(1.99)
Mostly be using: myself	0.257	0.332	-0.0755**
	(0.438)	(0.472)	(-2.02)
Mostly be using: spouse	0.436	0.322	0.114***
	(0.497)	(0.468)	(2.85)

Note: Characteristics of the friends chosen by the male seeds and the female seeds, with the corresponding z-statistics of the rank-sum test. Only variables with significant differences are reported.

be literate, have less savings, and are less likely to own a business. In Table 2.15, we run our main specification for the whole sample, the sub-sample of male household heads, and the sub-sample of female household heads. It is more difficult to precisely estimate the treatment effects for the female sub-sample because of the lower number of observations. However, we note that the effects of the network and communication treatments are comparable in both sub-samples. Regressions in columns 4, 5 and 6 investigate the effect of the gender treatment in each sub-sample separately. We note that in the male sub-sample (column 5), our gender treatment still has little effect. This excludes the possibility that the absence of a strong effect of the gender treatment results from a composition effect. Instead, it indicates that the mechanism we hypothesised and discussed earlier might not be in place.

In an attempt to explain why men did not discount female seeds in our setting, Table 2.16 looks at indicators of women's status. Our survey included a series of questions about gender norms in the villages. In the first set of questions, we asked respondents whether they believed a woman should ask permission from her husband or a family member before going out. Almost all household heads said that women should ask for permission to go to the health center, to visit a friend or to go to the market. On the other hand, answers to other questions reflect more egalitarian views. Only about 5% of the sample said that they never talked with their spouse about what to spend income on, and about two-thirds of the sample said they often had such discussions. In addition, virtually all households thought that women should have a say in how income is spent. Most respondents thought that it was definitively important that girls go to school. They further expressed the view that beating a woman was rarely justified. Finally, most respondents thought that women were as able as men to use new technologies. It appears that gender norms here give women some say in purchasing decisions, as well as when it comes to using new products. This might therefore explain why our gender treatment had little effect on willingness to pay.

Table 2.14: Summary statistics by gender of respondent.

	Male	Female	Difference
Year of birth	1970.1	1975.5	-5.414***
	(14.74)	(10.73)	(-4.24)
Number of children	3.787	4.114	-0.327*
	(2.086)	(2.032)	(-1.69)
Education	2.194	1.321	0.874***
	(1.411)	(0.895)	(7.29)
Expenses	4384.3	4298.7	85.52
	(3073.8)	(2303.3)	(0.32)
Savings	574.8	379.9	194.9**
	(965.0)	(684.9)	(2.34)
Owns a business	0.0741	0.0126	0.0615***
	(0.262)	(0.112)	(2.86)
Household size	7.449	6.748	0.701**
	(3.578)	(3.471)	(2.13)
Number of children to school	1.410	1.658	-0.248*
	(1.616)	(1.518)	(-1.67)
Read hindi	0.590	0.189	0.402***
	(0.492)	(0.392)	(9.26)
In debt	0.514	0.528	-0.0144
	(0.500)	(0.501)	(-0.31)
Land	1.456	1.207	0.249
	(1.668)	(1.993)	(1.53)
Irrigated land	1.406	1.158	0.247
	(1.603)	(1.981)	(1.56)
Owns cattle	0.903	0.862	0.0411
	(0.297)	(0.346)	(1.43)
Has a phone	0.856	0.843	0.0137
	(0.351)	(0.365)	(0.42)
Number of kerosene lamps	2.451	2.258	0.194*
	(1.189)	(1.154)	(1.77)
Hours of lighting	4.906	5.245	-0.339*
	(1.884)	(2.288)	(-1.83)

Note: 159 observations for female and 432 for male.

Table 2.15: Heterogeneity analysis by gender of the respondent.

	(1) All	(2) Male	(3) Female	(4) All	(5) Male	(6) Female
Network	119.883***	132.505***	131.282*	136.988***	134.586***	183.333
	(22.115)	(28.906)	(72.932)	(30.847)	(35.014)	(205.317)
Communication	195.078***	201.245***	173.572***	224.416***	224.802***	-58.333
	(22.925)	(30.216)	(64.552)	(32.086)	(36.442)	(207.667)
Network x Female Seed				-34.067	-10.586	-74.003
				(44.229)	(62.968)	(216.857)
Communication x Female Seed				-57.749	-63.893	261.340
				(45.745)	(65.971)	(217.925)
Habitation fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.157	0.161	0.144	0.161	0.165	0.191
Observations	585	426	159	585	426	159

Standard errors in parentheses
Dependent variable: Willingness to Pay.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.6 Conclusion

Adoption and diffusion of new technologies is crucial to improve the livelihood of poor communities. One important factor that promotes this process is information sharing through social networks. Adoption of a new technology is a social process because its adoption by an individual creates positive information externality to peers and this increases their expected welfare (Bardhan et al. 1999). Does rewarding individuals who make a conscious effort to communicate information about new technologies increase willingness to pay (WTP) by members of a social network? Whose social network in the household matters for the flow of information about new technologies? In this paper, we attempted to answer these questions by crafting a randomized controlled trial which involves distribution of multi-purpose solar lanterns under different treatments.

We collaborated with a local institution in rural India and assigned three peers of randomly recruited seed individuals (half of them male and half female) into a "network treatment", a "communication treatment" and a "control group". We elicited WTP for the solar lanterns from the control group right after interviewing the seed household, using the Becker-

Table 2.16: Descriptive statistics on women's status.

	Control	Network	Communication
1. Should ask permission to go the health center	0.975	0.959	0.954
	(0.158)	(0.198)	(0.209)
2. Should ask permission to go visit a friend	0.995	0.949	0.985
	(0.0712)	(0.220)	(0.123)
3. Should ask permission to go to the market	0.990	0.964	0.990
	(0.101)	(0.186)	(0.101)
4. Talk with spouse about what to spend money on	1.660	1.645	1.492
	(0.545)	(0.576)	(0.636)
5. Women should have a say on how to spend income	0.995	0.990	0.929
	(0.124)	(0.101)	(0.277)
6. It is important that girls go to school	4.985	4.980	4.959
	(0.214)	(0.141)	(0.222)
7. Women should work outside home or own a business	4.223	3.086	3.685
	(1.415)	(1.786)	(1.756)
8. Beating justified if she goes out without telling	0.594	0.497	0.497
	(0.492)	(0.501)	(0.501)
9. Beating justified if she argues with husband	0.589	0.624	0.680
	(0.493)	(0.486)	(0.468)
10. Beating justified if suspected of adultery	0.706	0.741	0.822
	(0.457)	(0.439)	(0.383)
11. Men are better able to use new technologies than women	3.452	3.264	2.924
	(1.712)	(1.657)	(1.738)

Note: Most variables are binary variables where 0 codes for no, and 1 for yes. Answers to question 4 are coded as follows: 0 for "Never", 1 for "Sometimes", 2 for "Often". Answers to questions 6, 7, and 11 are as follows: 1 for "Definitely not", 2 for "Not really", 3 for "Neutral", 4 for "Somewhat" and 5 for "Definitely".

Degroot-Marschak (BDM) method (Becker et al. 1964). We elicited WTP for the lanterns from the "network" group one month after the seed households had acquired the lantern. We also asked the seed households to invite one of the peers (the communication group) for a tea meeting to demonstrate and share their experience in using the lantern after a month, in return for an incentive payment of 100 rupees. We elicited WTP of the communication group after the tea meetings have taken place. The study area is non-electrified and households did not have previous knowledge about the solar lanterns. These facts allowed us to explore the flow of information and the value households place on technologies that have large potential to improve quality of life of all members of the household.

Our results show that households, who most likely learned about the solar lantern technology through their network (passive network), are willing to pay 120 Rupees more compared to the control group. Given the control group is willing to pay 134 Rupees on average, this corresponds to a 90% increase in WTP. On the other hand, households who attended a demonstration session by their peers (the communication treatment) are willing to pay 195 Rupees (145%) more than the control group. We do not find a statistically significant difference in WTP between male and female networks in either treatment. In order to shed light on the possible mechanisms that explain the observed outcome (WTP for the solar lanterns), we collected detailed information on peers' previous knowledge of solar lanterns, perception about their benefit, estimated market price, etc. Our results suggest that learning how to operate the technology and observing its benefits, which appeared to be superior to the kerosene lamp that households in the study area use as a source of lighting, are the important factors that drive WTP of both treatment groups.

Our findings have significant implications for policies that aim at promoting adoption and diffusion of new technologies in developing countries. If rewarding information communicator peers promotes information spill-over and willingness to pay, this implies that reducing the cost of the technology and allocating resources to communication will have significant welfare impacts on society. The results also highlight the potential role solar technologies could play in electrification. A significant proportion of households in developing countries do not have access to electricity and governments lack the required resources to extend the grid. Solar power has a large potential to tackle energy poverty by serving as a decentralized solution. In this regard, identifying the impact of incentivizing communication in inducing adoption and diffusion of such low-cost and environmentally-friendly technologies in rural settings provides useful information to policymakers and stakeholders who aim at improving the living conditions of poor households while protecting the environment.

Chapter 3

A Theoretical Model of Technological Change in Industrial Networks and Implications for a Green Technological Transition

Eugenie Dugoua and Marion Dumas

3.1 Introduction and Background

Various positive externalities impede the process of technological change at both the innovation and diffusion stages (Jaffe et al. 2003; Jaffe et al. 2005). These externalities usually justify using technology-push policies even though the precise type of policy is often debated (Steinmueller 2010). The market failure most commonly discussed in technology policy relates to the public good aspect of knowledge, and the early literature on this topic has demonstrated the need for subsidizing basic research efforts (Rockett 2010; Stephan 2010). Attention has also focused on issues faced by adopters such as dynamic increasing returns in learning-by-using and user network effects (Farrell et al. 2007; Liebowitz et al. 1994)[1].

Beyond issues of adoption by end-users is the growing recognition that manufacturing is a critical locus in the innovation process. Proofs of concept are not sufficient to guarantee success in manufacturing; product development through pilot and large-scale testings provide opportunities for valuable learning and adjustment that are critical to innovation (Bonvillian 2013). Learning and adjustments seem particularly important as products most often constitute complex combinations of components supplied by different firms (Fuchs 2014). Manufacturing is a time where all suppliers and producers make essential investments towards developing a new product. However, the most commonly discussed positive externality faced by producers, learning-by-doing, is a type of dynamic increasing returns that is internal to the firm (Thompson 2010); it remains blind to relationships between final producers and suppliers.

The importance of relationships between a final producer and its suppliers for innovation is widely acknowledged. Jorde et al. (1990), for example, argue that low levels of cooperation between firms result in low levels of innovation. Additionally, a large part of contract theory studies how the ability to contract between suppliers and buyers affects investment, and therefore innovation (Blanchard et al. 1997; Chen et al. 2011; Gilson et al. 2009). But

[1]Notable papers in this literature include (Besen et al. 1994; David 1997; Farrell et al. 1985, 1986; Katz et al. 1985, 1986, 1994).

this literature has focused on producer-supplier relationships within a linear vertical supply chain. It has yet to investigate the role that more complex industrial networks[2] can play in fostering or hindering technological change.

The importance of such networks for various economic phenomena, aggregate output and trade in particular, is gradually being recognized, and researchers are increasingly describing them theoretically and empirically (Acemoglu et al. 2012; Atalay et al. 2011; Carvalho 2014; Oberfield 2012). A 2008 Senate hearing testimony illustrates the critical role of shared suppliers: Ford's CEO advocated for the bailout of General Motors and Chrysler, Ford's principal competitors to protect their shared suppliers[3] (Carvalho 2014).

This paper investigates how supply-chain network characteristics impact firms' ambition to innovate. We develop a theoretical model to illustrate and examine a new type of positive externality where the cost of producing a new technology to one producer may depend on how many other producers are deploying similar technologies. We call such externalities *supplier network externalities*, and they can be thought of as a distant cousin to the typical user network externalities discussed in the technology adoption literature. For example, David (1985) discusses the factors that led QWERTY to become "locked in" as the dominant keyboard arrangement.

David (ibid.) argues that three factors played a key role: compatibility issues between a given keyboard and the typist's training, economies of scale, and quasi-irreversibility of investment. Those factors induced QWERTY's user costs to decrease as it gained acceptance relative to other systems. Eventually this led to the quasi-universal adoption of the keyboard. Importantly, network effects create multiple equilibria: users' expectations are often crucial in determining which network succeeds, and early preferences and information are likely to play an excessive role in determining long-term outcomes. For these reasons,

[2]More complex than just a linear node between a producer and a supplier; for example when two competitors share suppliers

[3]Mulally (2008): "In addition, the collapse of one of our competitors would have a severe impact on Ford and our transformation plan because the domestic auto industry is highly interdependent. It would also have devastating ripple effects across the entire U.S. economy".

the QWERTY example has sometimes been regarded as the 'founding myth' of the path dependence literature (Ruttan 1997).

We build our model on two main assumptions. First, we assume economies of scope in the supplier's technology. Consequently, the cost of producing intermediate inputs decreases with the number of producers sourcing similar inputs. Second, we assume that economies of scope may be lost when innovations require complementary investments from producers and suppliers. This is because producers might innovate in ways that are incompatible for the supplier. In what follows, we define *radical innovations* as innovations requiring investments from producers *and* suppliers (complementary investments).

The supplier network externality, hence, produces a positive externality leading to increasing returns in the numbers of producers deploying radical innovations: producer 1 has more returns from deploying radical innovations if producer 2 does as well and they can coordinate. In other words, unless all incumbent buyers switch to similar competing technologies and, therefore, buy the same new intermediate input, the supplier will lose part or all of its economies of scope. Our model, therefore, shows that shared suppliers can be reluctant to engage in radical innovations. But coordinating producers' innovation strategies would encourage shared suppliers to innovate.

A further implication of network externalities is that lock-in situations may arise, especially if barriers to moving to alternative competing technologies are high. In that case, producers would display excess inertia by waiting too long before switching. Absent coordination, such lock-in situations would lead to market failures when it is socially desirable to adopt a technological path different from the one that has been chosen by the market.

We argue this may be the case for green innovations, where the primary policy instrument to encourage innovation has been market instruments, which are not designed to solve coordination problems. First, we argue that many of the technologies needed to decarbonize the economy qualify as *radical*, particularly in the car manufacturing sector. Second, we argue our model is particularly relevant for this sector by showing that automakers often share

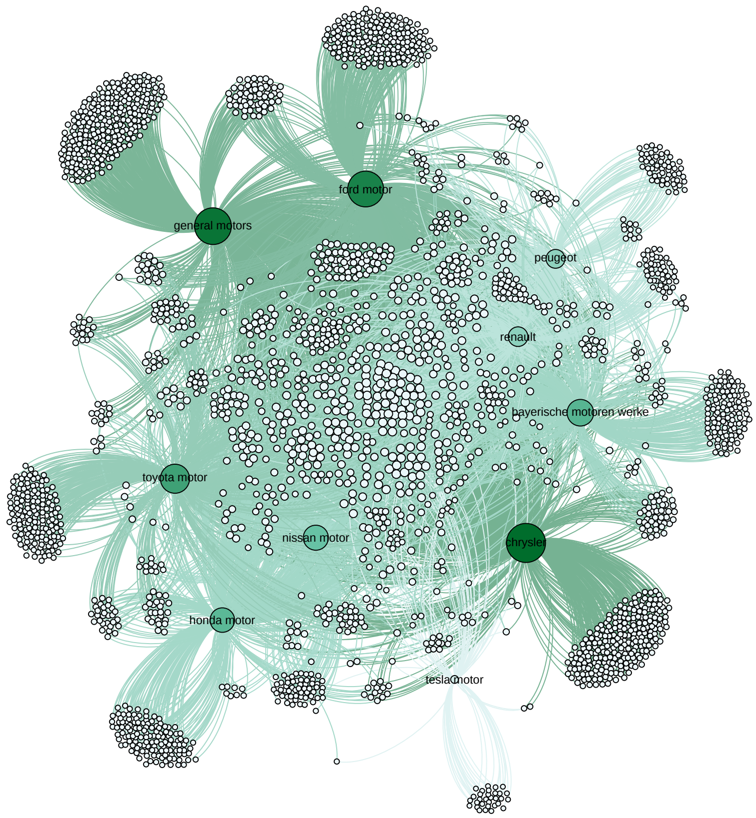


Figure 3.1: Supplier Network for Ten Car Manufacturers

Note: Each green bond denotes a buyer-supplier relationship. Nodes in the center are shared among two or more producers. The color gradient indicates nodes' number of links and the size of the nodes indicates their eigenvector centrality: we see that a large number of suppliers in the center are highly central.

suppliers. To do this, we use a database of buyer-supplier relationships, FactSet. Figure 3.1 illustrates the centrality of many suppliers. Finally, we show how our result helps unify several findings from case studies on the automotive industry.

The following section describes our theoretical framework, and Section 3.3 summarizes the main results. In Section 3.4, we discuss implications for a green technological transition.

3.2 Theoretical Framework

We model a network of two producers (denoted by subscript 1 and 2, respectively) and one shared supplier (denoted by subscript S). Each producer manufactures a good using inputs from the supplier. The demand function for the goods is derived from a model of discrete-choice demand that appropriately describes industries, such as car manufacturing, where typically products are differentiated, and consumers choose only one of the competing products (Anderson et al. 1992). In such a model, good 1 and good 2 are competing products which have quality a_1 and a_2. Aggregate demand for product 1 with quality a_1 is shown in Equation 3.1. U_0 is the utility derived from the outside option; M is the number of consumers (the size of the market); μ is the scale parameter of the i.i.d. type 1 extreme values distribution of $\{\epsilon_{kj}\}$ where ϵ_{kj} represents the idiosyncratic preference of consumer k for good j.

$$q_1(p_1, p_2, a_1, a_2) = \frac{e^{\frac{a_1 - p_1}{\mu}}}{e^{U_0} + e^{\frac{a_1 - p_1}{\mu}} + e^{\frac{a_2 - p_2}{\mu}}}.M \tag{3.1}$$

Since products 1 and 2 result from collaborations between producers and their supplier, improving the quality a_j can be done by either of the firms on its own or jointly with complementary investments. We build on the observation that some innovations require little change to the components of the previous product. For example, commercializing a fuel-efficient car requires changes within the engine, but all other components roughly remain the same. Producing a fuel-cell electric car, however, requires changes to many components (Zapata et al. 2010) produced by different firms. Following this example, we think of radical innovations as product changes that require investments from multiple firms because the skills, knowledge, and/or inputs needed to deploy the innovation are not present within the firm[4].

In the model, firms choose the degree of radicalness for a new product. We can also think of radicalness as the degree of "common effort" required to develop the new product (common within the supply chain). The more common effort required, the more radical the technology. We denote z_j the degree of "radicalness" that firm j chooses for a particular innovation, where $z \in [0; 1]$. If z_j equals zero, firm j chooses not to develop innovations requiring investments from other firms in the supply chain. The firm makes unilateral investments to innovate on the final product "on its own", and we can think of the innovation as being *marginal*.

In contrast, when $z_j > 0$, the innovation can be thought of as *radical* in the sense that it requires investments from multiple actors of the supply chain. As z_j increases, the ambition regarding how radical the innovation is, also increases.

As we said, what makes an innovation radical is that it requires common effort. We formalize that by assuming that the innovations of each player in the supply-chain are perfect complements: only the lowest degree of "radicalness" wished by all actors can be implemented. We denote $\hat{z}_j$ the resulting degree of "radicalness" in the supply chain of producer j:.

$$\hat{z}_j = \min\{z_j, z_S\} \tag{3.2}$$

We assume that innovations with more ambitious common effort bear the promise of higher quality a_j and, ceteris paribus, higher profits. As shown in Equation 3.3, a_j linearly increases with $\hat{z}_j$ according to a positive constant β. We impose that $\beta > 0$ to capture the idea that more ambitious innovations, while requiring more concerted efforts, also yield higher quality.

$$a_j(\hat{z}_j) = \beta \hat{z}_j, \tag{3.3}$$

Deploying an innovation also requires paying for the actual investments. We take these

[4] In that sense, a technology might be radical only in relation to a particular organization (Soskice 1997; Teece 1986) and the knowledge and skills for the technology exist in another firm or research laboratory.

as a fixed cost whose magnitude increases with the degree of effort. We denote R_j and R_S the fixed costs for producer j and the supplier.

$$\begin{cases} R_j z_j & \text{is the fixed cost for producer } j \\ R_S z_S & \text{is the fixed cost for the supplier} \end{cases} \tag{3.4}$$

The variable cost for producers is a function of the quantity demanded and is denoted $C_j(q_j)$, where q_j is a function of $p_1, p_2, \hat{z}_1$ and $\hat{z}_2$. We impose $\frac{\partial^2 C_j}{\partial q_j^2} \leq 0$ (e.g., $C_j = c * q_j$ where c is a positive constant).

We introduce the possibility that producers might radically innovate in ways that are very different from each other and which impose on the supplier the need for producing very different inputs. We can think of this in terms of *multiple technological directions*. For example, if producer 1 chooses to invest in plug-in electric cars, while producer 2 in hybrid vehicles or hydrogen cars. For the supplier, such directions are not compatible and will require different inputs.

Whether or not producers innovate in the same direction is a move of nature; we denote θ the probability that they do not. This is what we call *miscoordination*. The realization of θ will impact the cost function of the supplier, C_S. Indeed, one reason for which a supplier is often shared amongst multiple competing producers is that the supplier enjoys economies of scale and scope. To capture the effect, we assume the cost function is a CES function. The formal expression is shown in Equation 3.5: k $\in [0; 1]$ is a parameter governing the returns to scale; and $\rho > 0$ is a parameter governing the extent to which the inputs produced by the supplier are substitutable in the cost function[5]. Remember that q_1 is a function of $p_1, p_2, \hat{z}_1$ and $\hat{z}_2$.

$$C_S(q_1, q_2) = \left(q_1^\rho + q_2^\rho\right)^{\frac{k}{\rho}}, \tag{3.5}$$

The move of nature regarding the coordination of the producers impacts ρ such that under miscoordination, inputs are less and less substitutable in the cost functions as $\hat{z}_j$

[5] $\rho > 1$ corresponds to economies of scope from producing multiple products, $\rho = 1$ corresponds to purely substitutable products, and $\rho < 1$ corresponds to diseconomies of scope from producing multiple products.

increases. Consequently, the supplier loses economies of scope. Under coordination, inputs are purely substitutable ($\rho = 1$). Hence, we have the following cost functions.

$$C_S(q_1, q_2) = \begin{cases} C_S^m(q_1, q_2) = \left(q_1^{\rho'} + q_2^{\rho'}\right)^{\frac{k}{\rho'}} \text{ and } \rho \ = \rho - \sigma \hat{z}_j \text{ , with probability } \theta \text{ (Miscoordination)} \\ C_S^c(q_1, q_2) = (q_1 + q_2)^k \text{ , with probability } 1 - \theta \text{ (Coordination)} \end{cases} \tag{3.6}$$

We assume incomplete contracts between suppliers and producers. Hence, the producers and supplier choose their level of innovative investment independently. We further assume that firms share revenues ex-post and that they split revenues equally. Since we have only one supplier shared between two producers, in our model, the share received by the producer j, s_j, equals 0.5.

The sequence of the game is as follows: 1) All players choose radicalness z, which determines the quality $a_j = \beta * min\{z_j, z_S\}$ for each final product; 2) a move of nature determines whether the producers coordinate or miscoordinate on the direction of innovation, which then affects the marginal costs of production of the shared suppliers; 3) producers choose the price of their products; 4) revenues are divided between producers and suppliers according to the shares s_j.

3.3 Results

Nash Equilibria of the Innovation Game

In this section, we characterize the Nash equilibrium of the innovation game. We find that, if any level of radical innovation is profitable for one producer, given the radicalness of the other producer's innovation, then this producer innovates at the maximal level of radicalness. However, the supplier's choice constrains the producers and eventually determines the Nash equilibrium in this 3-player system.

Best Responses in the Two-Producer Game

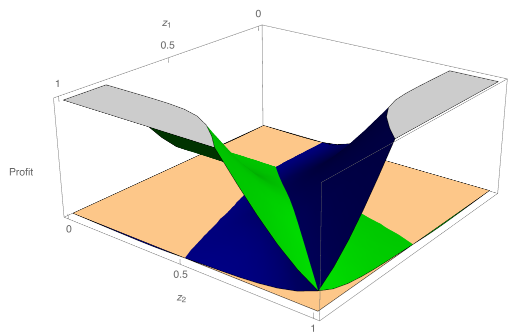
We first consider the innovation game between the two competing producers, assuming there is no supplier (or, equivalently, that the supplier innovates at the same level as each of the producers). Remark 1 below establishes the best response of producer 1 to the innovation level of producer 2, and vice versa. Π_j denotes the profit of firm j.

Remark 1. *We can distinguish two cases:*

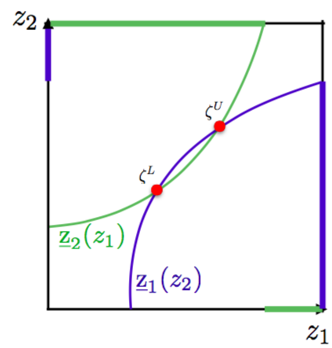
- *Either* $\Pi_1(z_1, z_2) < \Pi_1(0, z_2),\ \forall\ z_1, z_2$.
  In this case the best response is $z_1^{BR}(z_2) = 0$.
- *Or* $\exists\ \underline{z}_1$ *s.t.* $\Pi_1(z_1, z_2) \geq \Pi_1(0, z_2)$ *and* $\frac{\Pi_1(z_1,z_2)}{dz_1} > 0,\ \forall\ z_1 \geq \underline{z}_1, \forall z_2$.
  In this case, the best response is $z_1^{BR}(z_2) = 1$.

Figure 3.2 illustrates Remark 1. Panel 3.2a shows how the profit surfaces $\Pi_1(z_1, z_2)$ and $\Pi_2(z_1, z_2)$ vary with z_1 and z_2. For example, $\Pi_1(z_1, z_2)$ initially decreases[6] and then increases with z_1, becoming positive above some threshold value that depends on z_2. Panel 3.2b plots these threshold functions $\underline{z}_1(z_2)$ and $\underline{z}_2(z_1)$ in the (z_1, z_2) plane to identify regions where each producer can profit from doing radical innovation. For example, the blue curve $\underline{z}_1(z_2)$ delimits the area where profits for producer 1 are higher than the profits accrued if $z_1 = 0$. In Panel 3.2b, the blue curve crosses the y-axis below the top right corner: for any z_2 beyond that point, there exists no z_1 such that producer 1 profits can have profits higher than with $z_1 = 0$. Hence, above this point, the best response is $z_1 = 0$. On the other hand, to the right of the blue curve, we know that Π_1 increases with z_1 and therefore the best response level of innovation is 1. The best responses of each actor are shown in bold lines (for producer 1, it is the bold blue line). Depending on the parameters, the two curves may or may not cross. Figure 3.3 illustrates several possible cases. Assuming that they cross, it is useful for what follows to denote $\mathbf{\imath^L}$ and $\mathbf{\imath^U}$ the locus of these intersections.

[6] This is difficult to see on the graph, but the surfaces first go down below the pink horizontal plane.



(a) Example of profit surfaces as a function of the radicalness of innovations. The surface on the left-hand side corresponds to Π_1. The surface on the right-hand side corresponds to Π_2. $\Pi_1(z_1, z_2)$ initially decreases with z_1 and then increases with z_1, becoming positive above some threshold value that depends on z_2.



(b) The functions $\underline{z}_1(z_2)$ and $\underline{z}_2(z_1)$ above describe the threshold values above which profits are larger than when choosing $z = 0$. The thick lines represents the best response values for each player.

Figure 3.2: The profit functions and best response functions.

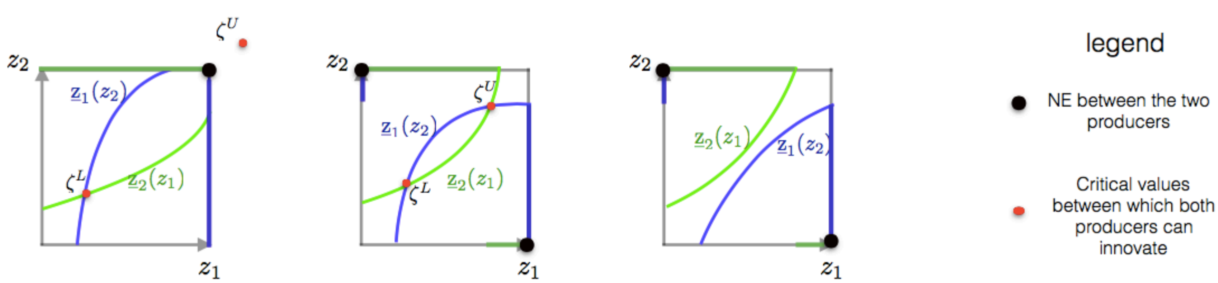


Figure 3.3: Diagrams showing different cases of Figure 3.2a. The bold and opaque colored lines represent the best response functions of both producers. The large black dots represent the resulting Nash Equilibrium.

Nash Equilibria in the Two-Producer Game

The possible Nash equilibria of the 2-producer game follow from Remark 1 and are illustrated on Figure 3.3.

Remark 2. *Assuming that* $\exists\ \underline{z}_j(0) \in [0,1]$ *for* $j \in (1,2)$, *we can distinguish two possible cases:*

- *there is a unique NE equal to* $(1,1)$ *iff* $\boldsymbol{\imath}^{\mathbf{U}} \geq (1,1)$
- *there are two NE equal to* $(0,1)$ *and* $(1,0)$ *if* $\boldsymbol{\imath}^{U} < (1,1)$ *or if* $\boldsymbol{\imath}^{U}$ *does not exist.*

The assumption that $\exists\ \underline{z}_j(0) \in [0,1]$ for $j \in (1,2)$ simply rules out scenarios in which the profit surfaces can not be positive in any part of the (z_1, z_2) in Figure 3.2. In other words, we consider cases where, at the very least, producer 1 would profit from innovating when producer 2 choose not to innovate. Remark 2 says that the NE is unique and equal to $(1,1)$ if and only if both producers find it profitable to innovate at the maximal level $z = 1$ simultaneously. Otherwise, we have an anti-coordination game in which one producer innovates maximally and the other innovates only marginally ($z = 0$).

Nash Equilibrium in the 3-Player Game

We are now ready to bring in the shared supplier. To simplify the analysis, we will focus on the first case above, where the NE of the 2-producer game is unique and equal to $(1,1)$. Note that the first diagram in Figure 3.3 illustrates this case. This allows us to focus on the case where, in the absence of supplier-buyer relationships, producers would both wish to innovate maximally. This approach presents the advantage of isolating the effects of those structural factors[7]. We also start with the symmetric case, in which producers have the same costs. We denote z_1, z_2 and z_S the levels of radicalness chosen by producer 1, 2 and the supplier, respectively.

[7] The reason it also simplifies the analysis is because, when $\boldsymbol{\imath}^{\mathbf{L}}$ and $\boldsymbol{\imath}^{\mathbf{U}}$ exist and lie within $[0,1] \times [0,1]$, the supplier can pick between different types of equilibria.

Remark 3. *In the symmetric case, the Nash Equilibria (z_1, z_2, z_S) of the 3-player innovation game are:*

$$\begin{cases} (0,0,0) \ \textit{or} \ (z_S^{max}, z_S^{max}, z_S^{max}) & \textit{iff} \asymp^L \leq z_S^{max} \\ (0,0,0) \ \textit{or} \ (\asymp^L, \asymp^L, \asymp^L) & \textit{iff} \ z_S^{max} < \asymp^L < \bar{z}_S \\ (0,0,0) & \textit{iff} \ \bar{z}_S < \asymp^L \ \textit{or} \ \Pi_S(z_S^{max}) < \Pi_S(0) \end{cases}$$

where z_S^{max} is the radicalness level that maximizes the expected profits of the supplier assuming she could dictate the level of innovation for other players ($E[\Pi_S(z_S, z_S, z_S)]$), and $\bar{z}_S$ is the threshold value above which expected profits of the supplier are negative.

Because innovation choices are perfect complements, $(0,0,0)$ is always a possible equilibrium, even if innovation is profitable. Therefore, the innovation game is a coordination game. We will come back to this in future work as we introduce more shared suppliers and analyze risk-dominant play. In what follows, we focus on explaining the equilibria with positive levels of innovation.

To understand Remark 3, consider Figure 3.4, which illustrates how the choice of the supplier interacts with that of the producers. As shown before, when producers do not depend on a supplier, they invest $z = 1$. Now, with a shared supplier and the assumption that the effective level of radicalness for producer j is $\hat{z}_1 = min\{z_1, z_S\}$, the optimal investment level for producer j is now $z_j = z_S$, as long as $z_S \geq \asymp^L$, and 0 otherwise.

Hence, the supplier faces an inequality constrained optimization problem: pick z_S such that $z_S \geq \asymp^L$ and such that her own profit is higher than with a marginal innovation level $z_S = 0$. Let us focus our attention on the 45 degree line in Figure 3.4. This line now represents the supplier's choice set, $z_S \in [0,1]$. Along this line, we plotted $E[\Pi_S]$, the supplier's expected profit function: it first decreases, then increases, reaching a maximum at z_S^{max}, and finally decreases turning negative at $\bar{z}_S$. If $z_S^{max} \geq \asymp^L$, it is feasible and leads to the $(z_S^{max}, z_S^{max}, z_S^{max})$ NE. If $z_S^{max} < \asymp^{\mathcal{L}}$, but $\bar{z}_S$ is still greater than $\asymp^L$, then the supplier can choose $z_S = \asymp^L$. Finally, if $\bar{z}_S < \asymp^L$, then the only NE is $(0,0,0)$.

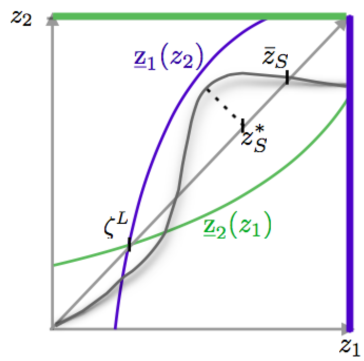


Figure 3.4: Diagram overlaying the supplier's profit function on the (z_1, z_2) plane. The order of the three points $\asymp^L$, z_S^{max} and $\bar{z}_S$ determines the Nash Equilibrium of the three-player game described in Remark 3

Effects of Miscoordination

We are now ready to state the main results regarding the effects of miscoordination between producers. We start with the finding that, as the probability of miscoordination θ increases, the NE level of innovation decreases. We saw in Remark 3 that at equilibrium, all players choose the same level of radicalness, which is "set" by the shared supplier. To simplify, denote this equilibrium level of radicalness z_S^*.

Result 1. *In the symmetric case, as the probability of miscoordination, θ, increases, z_S^* decreases and, by Remark 2, so do the equilibrium innovation levels of both supply chains.*

When θ increases, the probability that both producers innovate in different directions increases. When this happens, suppliers must produce different types of inputs for each of the producers and they become more vulnerable to losing economies of scope. Since higher radicalness leads to greater specificity in the inputs and thereby larger losses on economies of scope, suppliers decrease their ambition of radicalness. In the model, we capture the sensitivity of the production process to this miscoordination by σ; this coefficient governs how much radicalness affects the elasticity of substitution between the components supplied to both value chains in the case of miscoordination. Figure 3.5 illustrates these dynamics for specific parameter values. We note that, first, z_S^* decreases slowly; then comes a value of

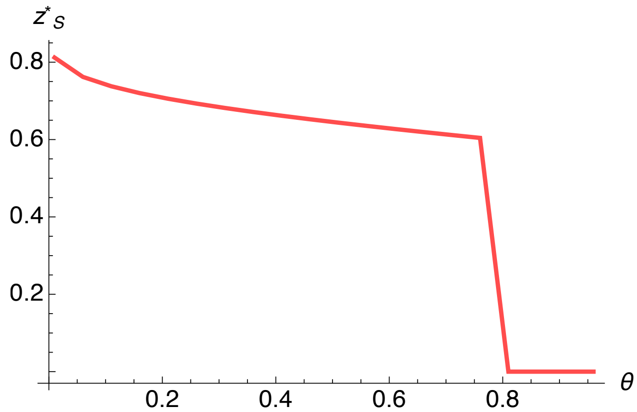


Figure 3.5: Change in z_S^* as a function of θ, in the 3-player case. The parameters describing the cost function of the supplier are $k = 1$, $\sigma = .9$

θ above which the supplier prefer zero degree of radicalness.

In what follows, we show that Result 1 is sensitive to the importance of economies of scale in the supplier's production process.

Result 2. *As the supplier's economies of scale increase, the negative impact of miscoordination on radicalness decreases. Formally:* $\frac{d^2 z_S^*}{d\theta \ dk} < 0$.

The reason for this result is that large economies of scale reduce the importance of production costs in the supplier's calculus. Also, because more radical innovation leads to higher demand and, therefore, greater production and greater economies of scale which can compensate the loss in economies of scope, or even diseconomies of scope.

Inducing innovation

In many cases, policy-makers wish to induce innovation, i.e. increase a specific quality a of a product, to meet a societal goal such as mitigating climate change. In the case of climate change mitigation, a would be the cleanliness of the product (its low level of carbon emissions). Several parameters in our model affect whether investing in this innovation will be profitable for the decisive player (here the shared supplier), which can be shaped by policy. First, there are parameters that govern the demand for the product: M the size of the market, and β, the marginal value of quality a to the customer's utility. M can be changed by procurement policies, while β can be changed by a carbon tax (which will increase the attractiveness of low-carbon products). Second, there are the parameters affecting the cost, and in particular, the marginal upfront investment cost R_S which can be shaped by subsidies. How does the risk of miscoordination affect the ability to induce innovation via these various policies?

Let $\bar{R}_S$ be the maximum upfront innovation investment cost at which the supplier wishes to innovate, (i.e. such that $E[\Pi^S](z_S^*, \bar{R}_S) = 0$). Similarly, let $\underline{\mathrm{M}}$ be the minimum market size for which the supplier wishes to innovate (analogously, the market size such that expected profit is exactly 0) and $\underline{\beta}$ the minimum marginal utility of quality for the consumer for innovating in quality to be profitable. In other words, these are the threshold values for key parameters that affect the parameter space under which innovation is attractive to the supplier.

Result 3. *In the 3-player game, we find that:*

- $\frac{d\bar{R}_S}{d\theta} < 0$
- $\frac{d\underline{M}}{d\theta} > 0$
- $\frac{d\underline{\beta}}{d\theta} > 0$

These three comparative statics results tell us that an increased risk of miscoordinating technological directions reduces the parameter space under which innovation is attractive to the supplier: all other things equal, if the miscoordination probability increases, the upfront cost cannot be as high, the market must be larger, and the marginal utility to the customer of quality improvements must be higher. In turn, if subsidies are used to induce innovation by reducing the upfront costs borne by the firm, these subsidies will need to be higher, while procurement policies to increase the market size would need to be more vigorous. Similarly, if the marginal utility to customers of products being green is raised by a carbon tax, then this tax needs to be higher.

These three results arise from the same straightforward logic having to do with their effect on the profit function: θ, R_S, β and M all affect the maximized objective function, so a movement in θ changes the threshold value of the other three parameters at which the objective function is positive. However, these three parameters – and the associated policy instruments that can shape them – have different effects on z_S^*, the chosen level of ambition in equilibrium. Hence, although in our model they can all induce a shift from no innovation to some innovation, they are not equally effective in encouraging a higher level of radicalness:

Remark 4. *In the 3-player game, we find that:*

- $\frac{dz_S^*}{dR_S} = 0$
- $\frac{dz_S^*}{dM} > 0$
- $\frac{dz_S^*}{d\beta} < 0$

Remark 4 indicates first that changing the upfront cost has no effect on ambition since it simply shifts the profit function. Second, increasing the market size also raises ambition. Third, raising β has the effect of *lowering* ambition. Hence, although β needs to exceed some minimum level, raising it further can be counter-productive. We interpret this as a note of caution regarding the reliance on carbon taxes to induce innovation, at least within the limited scope conditions of this model. This result stems from two properties of the model: 1) customers compare the products to the utility obtained from some outside option, so as β increases, a lower quality is needed to compete successfully with that outside option; 2) the supplier chooses the level of ambition unilaterally, so beyond the level of quality that successfully draws customers away from the outside option, the supplier has no more competitive incentive to further increase quality.

Although quite minimal, our model illuminates a few interesting tensions that arise when there exist technologically critical suppliers that are shared between competing producers:

1. Although there is competition between producers in price or quantity of the final good, the presence of a shared supplier can create a monopoly-like position upstream in the

supply network with regards to innovation choices, and this, in fact, can discourage innovation.

2. If there is a risk that producers will innovate in substantively different ways (miscoordinate their technological direction), shared suppliers will be more reluctant to innovate and they will innovate less ambitiously, for fear of losing their central position in the supply network.
3. This probability of miscoordination between producers reduces the size of the parameter space that supports positive innovation. Consequentially, inducing innovation in the network requires more ambitious policies (such as procurement, subsidies or taxes) when this risk of miscoordination is high.

We see that the network structure underlying production matters for understanding the incentives to engage in radical innovation. Specifically, the model illustrates a case in which attaining higher levels of innovative ambition requires that producers be able to coordinate their technological vision so as to align the suppliers they co-depend on for the success of the innovative projects.

We will now examine the implications of the model for green technological transitions, with a focus on the car manufacturing sector and a discussion of mechanisms to foster coordination between industrial actors.

3.4 Implication for a Green Technological Transition

Climate Change Mitigation Requires Radical Technologies

The last IPCC report asserted that, if the world wants to limit anthropogenic warming to less than two degrees Celsius[8], greenhouse gases emissions need to decrease to zero net emissions

[8] with more than a 50% chance

by 2100[9] (IPCC 2014). Many argue that revolutionary changes in technology are needed to achieve such objectives (Hoffert et al. 2002). For example, Barrett (2009) argues that the needed change looks like a technological "revolution" because it "will require fundamental change, achieved within a relatively short period of time." We agree with the statement, but for different reasons.

We think that the "revolution" consists less in bringing some technologies from paper to proofs of concept (e.g. nuclear fusion), and more in pushing advanced technologies through the challenges of mass-scale production and diffusion. In that spirit, Pacala et al. (2004) have claimed that much could be achieved with what is already known (at least up the first half of the century). Similarly, the Deep Decarbonization Pathway Project attempts to demonstrate that, by relying on what we already know, the world can achieve a reduction between 70% and 100% by 2100 (Deep Decarbonization Pathways Project 2015).

These pathways don't rely on any R&D breakthrough. But they require fast and massive scaling-up of production and diffusion of advanced technologies. For example, they project emissions for passenger transport peaking around 2020, and about 134 million electric vehicles in 2030[10]. Much of this change requires that large networks of firms redirect their production towards radically different products. We argue in this paper that coordinating downstream producers is critical for technological transitions to take place. To further our point, we focus on the car manufacturing sector in the following section.

The Case of the Automotive Industry

The automobile is a complex product for which parts and sub-parts that interact are often produced by different firms (MacDuffie et al. 2010). It is not surprising then that supplier-buyer relationships in this industry have received some high degree of scrutiny. For example,

[9]The reports states that emissions shall decrease between 40 to 70% by 2050 relative to 2010 and to zero net emissions by 2100

[10]together with 75 million plug-in hybrid electric vehicles, 31 million hydrogen fuel cell vehicles, 27 million compressed pipeline gas vehicles

Dyer (1996) attempted to quantitatively study how relationship specialization throughout the supply chain impacts performance measures such as quality or speed of new product development for Japanese and American automakers. For our argument, however, it matters critically that producers *share* suppliers. Since this particular aspect of the industrial organization has not been quantitatively documented, we turn to FactSet Revere[11], a database of supply chain relationships.

Table 3.1: Summary statistics on the number of suppliers in the car manufacturing sector

	mean	sd	min	max
Total number of suppliers	85.58	81.12	1.86	262.40
Percent shared	80.84	16.14	30.15	100.00
Percent not shared by any other producer	18.81	16.18	0.00	69.62
Percent shared by 2 to 5 producers	32.37	15.24	12.90	79.17
Percent shared by 6 to 9 producers	18.70	7.13	0.00	26.67
Percent shared by at least 10 producers	30.12	16.67	0.00	59.67
Relationship mean duration (in years)	6.00	1.46	1.80	8.02
Relationship max duration (in years)	12.10	4.17	2.00	15.00

Note: The summary statistics are for a sample of 35 car manufacturers using FactSet relationships from 2003 to 2017. Variables are first averaged across years to then generate summary statistics for a cross-section of producers. The "total number of suppliers" for a given producer j is the yearly average of the number of suppliers working with producer j. The variable "relationship mean duration" for a given producer j equals the yearly average of the average duration of all relationships observed in a given year for producer j. Accordingly, the variable "relationship max duration" for a given producer j equals the yearly average of the maximum duration of all relationships observed in a given year for producer j.

We use FactSet Revere relationship database to obtain information on buyer-supplier relationships for car manufacturers. More information on data collection and cleaning is available in Appendix 3.6. Table 3.1 displays summary statistics for the buyer-supplier relationships. First, we note, in an average year, the average car manufacturer 1) works with about 85 different suppliers and, 2) shares about 80% of those suppliers with its competitors. This indicates that 1) the industry is heavily relying on outsourcing for manufacturing intermediate parts, and that 2) shared suppliers are the norm rather than the exception. We should highlight that, on average, about 30% of a car manufacturer's suppliers are shared

[11] `www.factset.com/data/company_data/supply_chain`

by 10 or more of its competitors. Hence, it appears that some suppliers could be labeled as "mega-suppliers", i.e. supplying most of final producers in the sector. The columns "min" and "max" in Table 3.1, however, are a testimony to significant variation across manufacturers with respect to their supply-chain organization. Figure 3.6 illustrate this point by showing that, although a group of ten or so manufacturers seem to share many suppliers, others in the industry are less connected.

Table 3.1 also provides summary statistics regarding the duration of the relationships between producers and suppliers. The relationships with suppliers have been going on for about six years on average (in the average year and for the average producer). The maximal duration observed for a relationship, however, is as high as about 12 years. This indicates that buyer-supplier relationships in this industry seem rather stable on the long-term, which would consistent with more asset-specific product development.

This structure, in fact, reflects the wave of outsourcing and "de-verticalization" that transformed the industry since the mid-80's (Sturgeon et al. 2008). Driven by a need to reduce cost in a globalized market, as well as a conviction that they should emulate the modular structure of the computer industry, producers increasingly outsourced the manufacturing of parts. They spun-off some of the subsidiaries producing intermediate parts, and some suppliers merged giving rise to the "mega-supplier" supplying complex modules to multiple producers (Jacobides et al. 2016). For example, in the 1990s, Nissan announced it would source components from one of Toyota's supplier, Denso (going against a long-standing norm that suppliers should not be shared between two rival supply chains or *keiretsu*). Denso had lower cost thanks to Toyota's large market share which provided greater economies of scale.

If, as we argue in this paper, shared suppliers are obstacles to innovation, why do car manufacturers rely so much on them? It is important to highlight here that the outsourcing wave took place jointly with a move towards greater standardization of intermediate inputs. Ahmadjian et al. (2001) describes this phenomenon for the Japanese automotive industry in the 1990s. A simple answer to our question is that shared suppliers are very efficient when

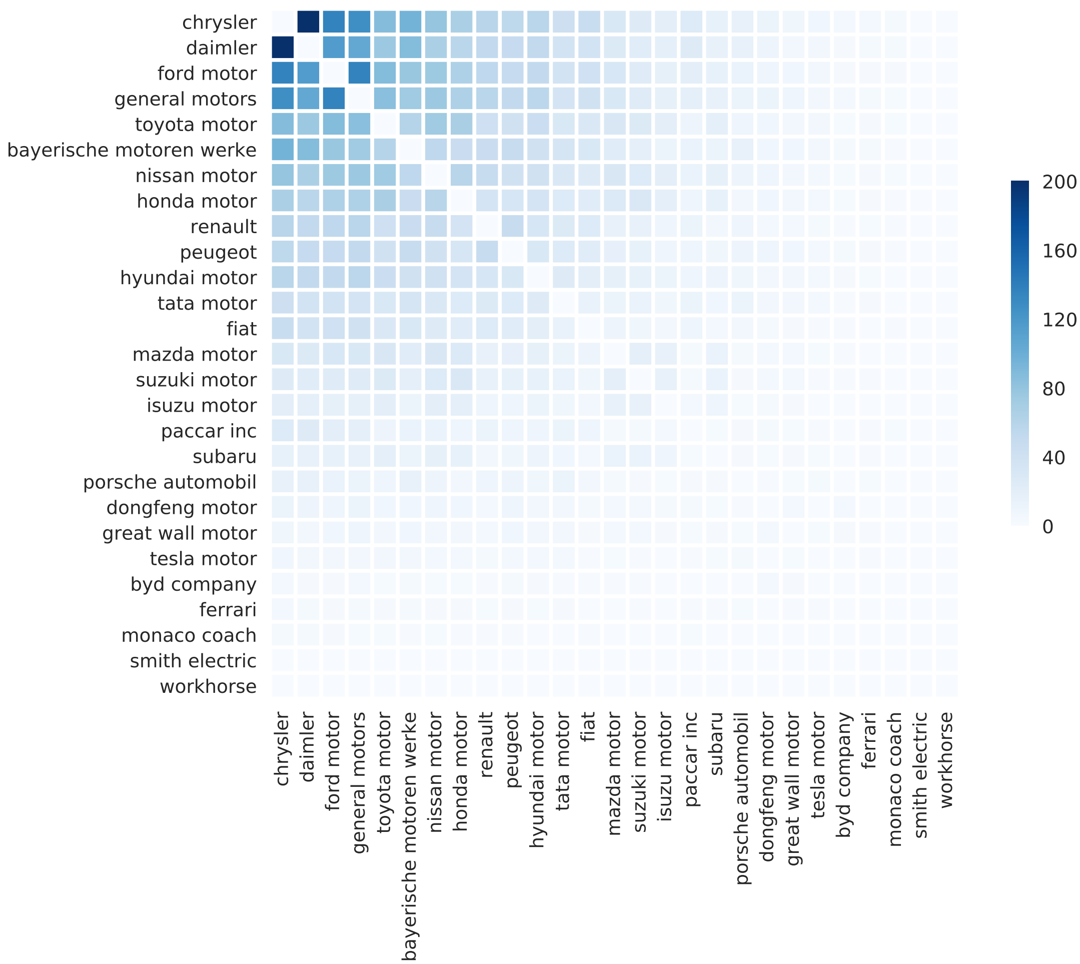


Figure 3.6: Number of Shared Suppliers

Note: Producers with no declared suppliers were dropped.

intermediate inputs have become standardized and innovation is minimal.

Alternatively, Jacobides et al. (2016) use case studies and historical research to argue that the outsourcing wave was partially a strategic mistake in the U.S. and Europe. Manufacturers saw the idea of outsourcing whole modules to capable suppliers as a new strategic imperative but overlooked contractual risks. Specifically, they put themselves at risk of surrendering power to mega-suppliers becoming strategic bottlenecks. Soon, the limits of the paradigm became apparent, and manufacturers became wary of shared suppliers. The following quote, from a Fiat executive, highlights that manufacturers believed suppliers lacked incentives to innovate: "It's all a question of money – suppliers can't imagine spending lots of money. The mega-suppliers want only big volume, they want to stick with processes they know. Their short-term incentive is to stay focused on components. [...] They are not likely to offer us their latest technologies if that threatens their existing investments – this can be a barrier to our innovation." (quote from Jacobides et al. 2016).

The state of affairs described above can be contrasted with somewhat savvier management of supplier relationships by Japanese auto-makers. As we saw, Nissan broke the long-standing Japanese *keiretsu* norm of not sharing key suppliers by starting to source from Denso, Toyota's main supplier of electronics. However, when it became clear that electronics were becoming a central and complex component of car technologies (requiring strong technological coordination), Toyota invested heavily in its internal capacity to manufacture electronics in order to lessen its reliance on Denso and to better monitor and control its dealings with its supplier, who now has split loyalties (Ahmadjian et al. 2001).

These case studies highlight that shared suppliers pose strategic problems in the process of innovation and, our data shows that these relationships abound. We ask: What are the consequences for the low-carbon transition? With the realization that the traditional combustion-engine-based car is responsible for a significant share of greenhouse gases emissions, the car manufacturing sector is in a period of ferment with many alternative powertrain technologies under testing (Sierzchula et al. 2012)[12]. Our model suggests that this multitude of technology directions exacerbates the strategic problems documented above, as the "mega-suppliers" have neither the incentive nor the capacity to make the requisite complementary investments, especially given the risk arising from the uncertainty in technological directions.

Empirically, we see that although most major manufacturers have announced ambitious plans for new clean products, investments in these new models still seems limited and driven by compliance with regulatory mandates. For example, Wells et al. (2012) argue that current

[12]Sierzchula et al. (2012) documents eight different competing technologies.

electric vehicles tend to be of inferior quality because the architecture of most models has not been sufficiently adapted to the new requirement of batteries. Critically, the industry has not scaled up its production and sales to the level hoped for by the Obama administration when it decided to make sizable investments in the battery supply-chain (Canis 2013). To our knowledge, there currently exists no rigorous case studies examining different firms' decisions to innovate in alternative vehicles and how those decisions are shaped by the scope of the firm, and the contracts and relationships with key partners. Such case studies are needed to understand progress in the low-carbon transition and our model provides some hypotheses to be tested in such case studies.

According to our model, we would expect that the players best positioned to make innovative and successful investments in alternative vehicles would be either firms with long-term relationships with their main suppliers, capable of co-design via relational contracts, such as Toyota, or vertically integrated firms. Interestingly, Tesla, which arguably is one the most innovative and successful producer of electric vehicles, is a new entrant, free from linkages with the historical network of suppliers. According to Dyer et al. (2015), it is also to a large extent vertically integrated. In their 2015 Forbes' article, Dyer et al. explained that Tesla initially tried to set up a global supply chain to reduce costs, but having manufacturing so spread out led to 'massive coordination problems'. The authors highlight that, compared to other car makers, Tesla manufactures many more components in-house, and they further argue this was a great advantage for bringing electric cars to the market because the pace of change was too fast for its suppliers to follow. So far, although Tesla successfully brought to market electric vehicles, those have yet to reach the status of mass-production. The firm has announced it would do so with the next model (Model 3), but many hurdles seem to lie ahead (Economist 2016).

3.5 Discussion

Our model shows that, under the presence of supplier network externalities, a transition to radical innovations is likely to take place only if producers coordinate in ways that create economies of scope for their suppliers. In the context of user network externality, the role of expectations is often highlighted for coordinating actors (Farrell et al. 2007). Naturally we might wonder: what kind of institutions or policies can effectively affect expectations?

Lately, the fight against climate change has called comparison to JFK's moonshot, stressing the importance of goal-setting and planning (Sachs 2015). The Sustainable Development Goals, voted by all countries represented at the United Nations in 2015, can be thought of as an example of goal-setting, and the Deep Decarbonization pathways, mentioned earlier, as examples of planning efforts. Such initiatives could, to a certain extent, be interpreted as "soft" mechanisms for modifying expectations about green transitions. Similarly, although the Paris Climate Agreement remains a non-binding set of pledges to reduce greenhouse gases emissions, it possibly is useful to foster the convergence of expectations of political and economic actors.

Importantly, the need and challenges of corodinating industrial actors echoe studies of the Defense Advanced Research Projects Agency (DARPA) (Fuchs 2010) and discussions about how to replicate it in the energy sector (Anadon et al. 2014; Bonvillian et al. 2011; Fuchs 2009; VanAtta 2007). Specifically, Fuchs (2010) shows how DARPA facilitates coordination among competitors and describes DARPA's technology policy as "embedded government agents" that re-architect social networks among researchers with the goal of identifying and influencing new technology directions, neither the invisible hand of the market nor picking winners. Althought DARPA's original strategy was focused on researchers, the agency swithced its focus to industry after 2001. According to Fuchs (ibid.), DARPA then supported the coordination of technology development across a vertically fragmented industry in whose direction the military has interest and in which long-term coordination of technology platforms was particularly challenging. DARPA actions mainly consisted in bringing together established vendors with academics and start-ups with the goal to support knowledge-sharing within industry, between competitors.

A quote from an industry participant at a DARPA seminar illuminates the dynamics at stake: “You just can’t make anything happen in industry (today) on your own, because it’s completely impossible. You have to find a partner, you have to convince your competition this is the right thing to do. You’re guiding people [your competitors], ... and they ask, ‘Why are you helping me with this?,’ and the fact is you give them information so the suppliers are in the right place to help you.” Here, the industry actor quoted by Fuchs (2010) clearly makes reference to the importance of coordinating supply chains, and in particular shared suppliers, in the hope of fostering technological change in the industry.

3.6 Conclusion

To foster green technological change, the economic literature proposes policies rectifying the market failures well-known to environmental and innovation economics (**Hallegatte.etal2011**; Jaffe et al. 2005; Popp 2010b; Popp et al. 2010). On one hand, the negative pollution externality imposed by greenhouse gases calls for a carbon price either through a tax or an allowance trading scheme. On the other, as discussed in this paper, various positive externalities also impede the process of technological change. It is, as a result, commonly accepted that a carbon tax alone will not be sufficient (Lehmann 2012; Lehmann et al. 2013). We contribute to this literature by suggesting an additional mechanism, supplier network externality, for producing sub-optimal technological transitions. Under the presence of such externalities, a transition to radical innovations is likely to take place only if producers coordinate in ways that create economies of scope for their suppliers. Finally, we argue that this case is relevant to car manufacturing sector and highlights connections to the literature debating the merits of innovation agencies such as DARPA. In the future, we intend to further investigate the policy implications of our model and extend our theoretical results. Specifically, we plan to generalize the model by allowing for m producers and n shared suppliers. With more than one shared supplier, the problem of coordinating on the equilibrium that features positive levels of innovation becomes salient and interesting for us to analyze. We can use an intuitive generalization of risk dominance (**Morris.etal1995**) to analyze how an increase in the number of players interacts with the parameter θ to change the overall likelihood of technological change in the system.

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Appendix to Chapter 1

Cleaning procedure

Full-text

For most articles, the full text downloaded from ScienceDirect requires many different cleaning steps before it can be analyzed. The text is often the imperfect result of the conversion of images of typed or printed text into machine-encoded text: some words are not well recognized especially when the article contained mathematical symbols and equations. Words are also sometimes not properly separated by space. Below are the successive cleaning steps I undertake. Patent texts require only a few preprocessing steps described below under the *preprocessing* section.

Preprocessing. I fix "broken" unicode such as garbled HTML entities, convert non-ascii characters into their closest ascii equivalents, replace all URL strings with "URL", replace all email strings with "EMAIL", replace all phone number strings with "PHONE", replace all currency symbols with their standard 3-letter abbreviations, replace English contractions with their non-shortened forms, replace all accented characters with unaccented versions. This is done through the use of the Python package *Textacy*. I also remove any sequence of more than 1000 digits. I also remove tokens with more than 50% of characters being digits.

Drop non-English articles. Some articles seem not to be written in English. For this reason, I use Google's CLD2 library in Python to detect every document's language, and drop those that are detected with large enough confidence as not being English.

Splitting text into sentences. I use the Python package *Spacy* to parse the text and detect sentences.

Clean each sentence. I remove any punctuation and tokens of length 1 (i.e. standalone characters). I also drop sentences if their number of non-digit tokens is lower than 5. This helps remove unintelligible sequences of letters and digits that are often found at the beginning of articles. Finally, I remove the entire sentence if less than 80% of tokens are recognized by SpaCy's English dictionary. This provides a rough test for whether the sentence is written in another language. Indeed articles can sometimes present translations in other languages within the full text.

Further processing. Number-like strings are replaced with the token "*NUMBER*". All words are lowercased.

Meta-Data

Scopus's meta-data provides the name and geographic localization of the authors' affiliations. However, Scopus does not provide information about these organization. In particular, knowing the share of articles affiliated with public vs. private entities would be interesting.

To that aim, I leverage the Global Research Identifier Database[13] (GRID) which provides

[13] `https://www.grid.ac/`

information about a worldwide collection of organizations associated with academic research. In particular, GRID classifies an entity as one of the following types: education, company, government, facility, non-profit, health care[14]. An organization is classified as "education" if it can grant degrees, as "company" if it is a business entity with the aim of gaining profit, as "government" if it is operated mainly by a government, and as "health care" if it is a place that treats patients. Facilities encompass building or facilities researching specific areas and usually containing specific equipment (e.g., a nuclear plant). Nonprofits include charities but also non-governmental research institutes[15].

Unfortunately, the name of the organizations and its geographical location are often reported differently in Scopus and GRID. To match as many entities as possible, I first look for exact matches, then for approximate ones using tools such as fuzzy matching in python. Still, many remained unmatched. I then manually match any organization appearing, at least, three times or more in the data. There were about 300 of such organizations.

The bulk UPSTO downloadable data contains patent meta-data. Names and addresses of the inventors and assignee are therefore more readily available. I use the country of the assignee, and when the patent has no assignee, I use the country of the inventor. The USPTO data, however, does not classify assignee concerning the type of the organization (e.g., company, education or non-profit). The GRID database here is not as useful because most patents originate from businesses; GRID encompasses some for-profit entities with major research activities, but many patentees are in fact small companies unlikely to be listed under GRID. Hence, to match patent assignees to a type, I implement a more basic strategy. It is useful to notice that the name of an organization tends to contain tokens informing about the nature of that organization. For example, the "Inc." abbreviation in the name *Flow Vision, Inc.* tells us that this is a for-profit organization. Other such tokens includes "corp.", "co.", "plc", "llc", "limited" or "company", as well as "& cie"[16]. Similarly, I identify organizations containing tokens such as "university" or "school" as being of the "education" type, and those containing tokens such as "govern", "ministr" or "agency" as being of the "government" type. The use of these simple rules helps me match about 36529 out of 45820 assignee names. Out of the 7899 remaining, I manually match those that appear at least ten times in my data (about 200 of them). I leave the rest with no type information.

Topic Modeling

I use topic modeling, a machine learning method for text analysis, to generate covariates that describe the semantics surrounding molecules and therefore proxying some chemically and industrial characteristics. Specifically, I use Latent Dirichlet Allocation (LDA), a method of probabilistic topic modeling for text (**Roberts.etal2014b**; Blei 2012; Blei et al. 2006, 2009; Roberts et al. 2016).

[14]There are two other classifications: "archive" and "other." For more information, see `https://www.grid.ac/pages/policies`

[15]For example, in the USA, the National Academy of Sciences is classified as a non-profit.

[16]In other languages, here are a few of the tokens that I found in the data: "kaisha" or "kk" in Japanese, "spa" in Italian, "gesellschaft" or "gmbh" or "ag" or "kg" in German, "bv" or "nv" in Dutch, "sa" or "sarl" in French, "ab" in Swedish, "oy" in Finnish, "rt" in Hungarian.

In this method, the experimenter chooses the number of topics, and after training the algorithm on a corpus, the model can return the topic distribution for each document. Put differently, using the words that appear in a given document; the LDA model infers what proportion of each topic a document contains. Intuitively, the topic proportions describe quantitatively what an article talks about, and we can, therefore, think of it as a proxy of the physical, chemical and industrial characteristics of a molecule. I train the algorithm, not on the entire corpus, but on the subset of documents that contain at least one mention of a molecule: this represents a total of 382,599 patents and 382,005 articles. The LDA model is trained choosing five topics. Table A1 displays the top three words in the five topics generated by the LDA model on the corpus of patents[17].

I then aggregate the topic proportions of the documents at the molecule level by calculating a weighted mean topic proportion with weights proportional to the number of times an article mentions a molecule. As a result, articles with many mentions of a molecule contribute more to the aggregated topic proportion. I also test the robustness of my results to taking a simple non-weighted mean. Figure 1.1 summarizes these various steps with a simple example of three documents, two molecules, and two topics.

Finally, I use these topic proportions together with the outcome variable (log count) as covariates in the synthetic control method. Hence, the algorithm will construct a synthetic control that not only reproduces the path of log count in pretreatment periods but that also mimics the values of the different topic proportions.

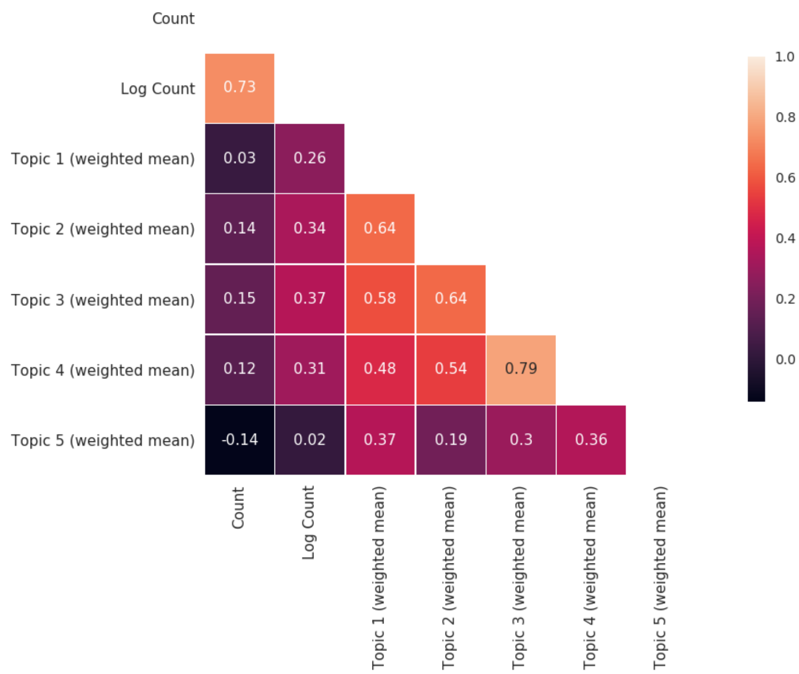
Figure A1 displays the correlation heat map between the topic proportions and counts in patents and articles. We note that the topic proportions are only weak predictors of the variable count. Hence, in the SCM optimization, they should have a small contribution in constructing the synthetic control because the SCM algorithm assigns bigger weights to variables that are better predictors. Figure 1.8, however, illustrates why topic proportions are still useful. The graphs display scatter plots of topic proportions and log count. We see that some HAPs have values of topic proportions that stand out as outliers. This indicates that those HAPs present a semantic context that is likely very different from the one of CFC substitutes. Hence topic proportions ensure that such HAPs are not used in constructing a synthetic control.

[17] The appendix features the lists of top 20 words for patents and articles.

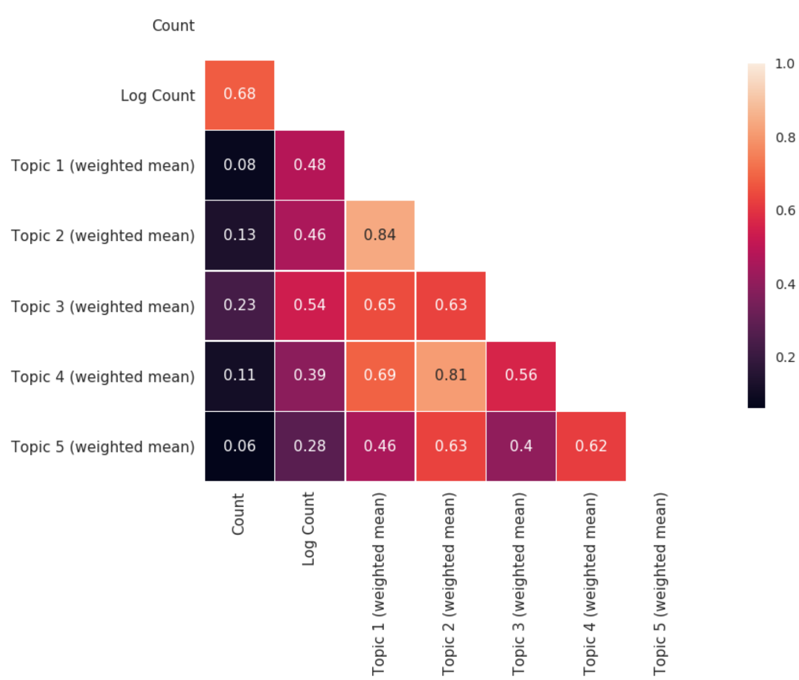
Table A1: Top 3 words in topics for patents

	Words	Probability
Topic 1	crotononitrile	0.0090
	remote	0.0063
	dialkylhydantoin	0.0047
Topic 2	andreu	0.0141
	sulfon	0.0075
	phosphatidylinositols	0.0072
Topic 3	neal	0.0323
	isopropyltrimethoxysilane	0.0276
	inducers	0.0236
Topic 4	topcoatings	0.0071
	heterophasic	0.0054
	neal	0.0052
Topic 5	trisethyl	0.0157
	maker	0.0128
	amineprotecting	0.0066

Note: The table presents the three most probably words in the five topics generated by the LDA algorithm. As a consequence of the nature of the corpora (patents), the words in the topics are highly technical and specialized which makes it difficult to associate one topic to a general theme.



(a) Patents.



(b) Articles.

Figure A1: Correlations between topic proportions and counts

Note: We see that topics somehow correlate with log counts. This will ensure that they contribute to the synthetic control. The whole sample is used.

SCM theoretical foundations

Here, I briefly summarize the theoretical underpinnings of the SCM. Suppose there are J+1 molecules, J molecules as potential controls and one, denoted with the subscript 1, that is treated. The treatment effect can be written as $\alpha_{it} = Y_{it}^T - Y_{it}^N$, where Y_{it}^N is the number of document mentioning molecule i in year t if no intervention, and Y_{it}^T the number of documents mentioning molecule i in year t if intervention. Here the quantity we need to estimate is Y_{it}^N. Abadie et al. (2010) show that a weighted average of the control units can approximate the counterfactual Y_{it}^N, that is:

$$Y_{1,t}^N \rightarrow \sum_{j=2}^{J+1} w_j^* Y_{jt} \text{ with } w* \text{ s.t. } \sum_{j=2}^{J+1} w_j^* Y_{jt} = Y_{1,t} \text{ and } \sum w_j^* Z_j = Z_1$$

To understand why this is the case, Equation 7 presents the underlying factor model. δ_t is an unknown common factor w constant loadings across units; θ_t is a vector of unknown parameters; Z_i a vector of observed covariates (not affected by intervention); λ_t unobserved common factors; μ_i a vector of unknown factor loadings and ϵ_{it} unobserved transitory shocks with zero mean. Note that this model generalizes the difference-in-differences model which imposes that λ_t be constant for all t. Hence, the unobserved confounders are constant in time and can be eliminated by taking time difference. Here, the SCM allows the effects of confounding unobserved characteristics to vary with time; taking time differences would not get us rid of μ_i.

$$Y_{it}^N = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \epsilon_{it} \tag{7}$$

A synthetic control such that $\sum_{j=2}^{J+1} w_j^* Z_j = Z_1$ and $\sum w_j^* \mu_j = \mu_1$ would be unbiased estimator of Y_{1t}^N. In other words, fitting Z_1 and Y_{11} ... Y_{1T_0} is a way of indirectly fitting μ_1, the unobserved factor loadings. As a result, it is important to restrict the donor pool to units with outcomes that are thought to be driven by the same structural process as for unit representing the case of interest and that were not subject to structural shocks to the outcome variable during the sample period.

Supplementary Tables and Figures

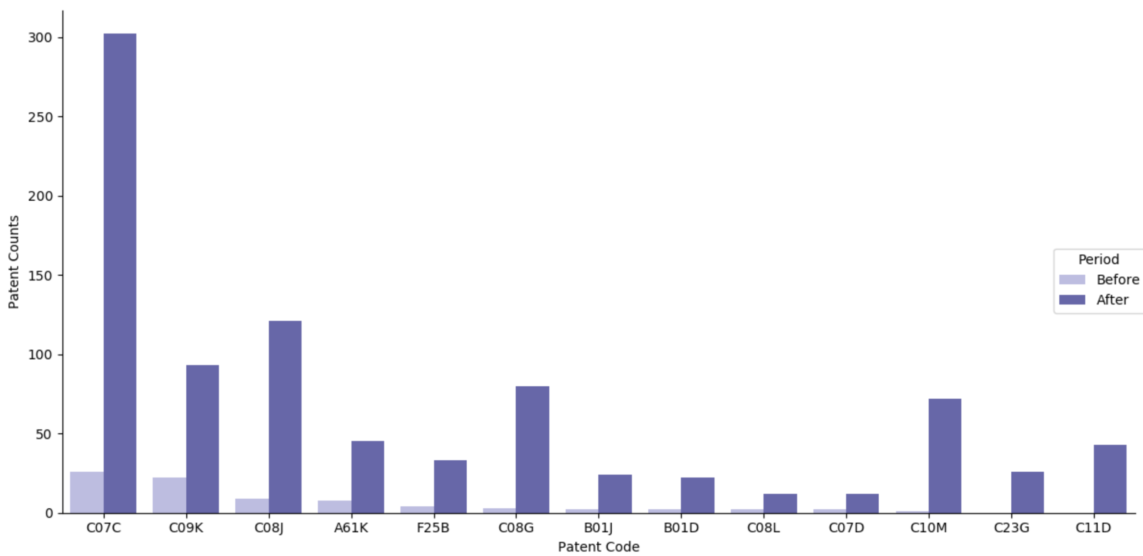


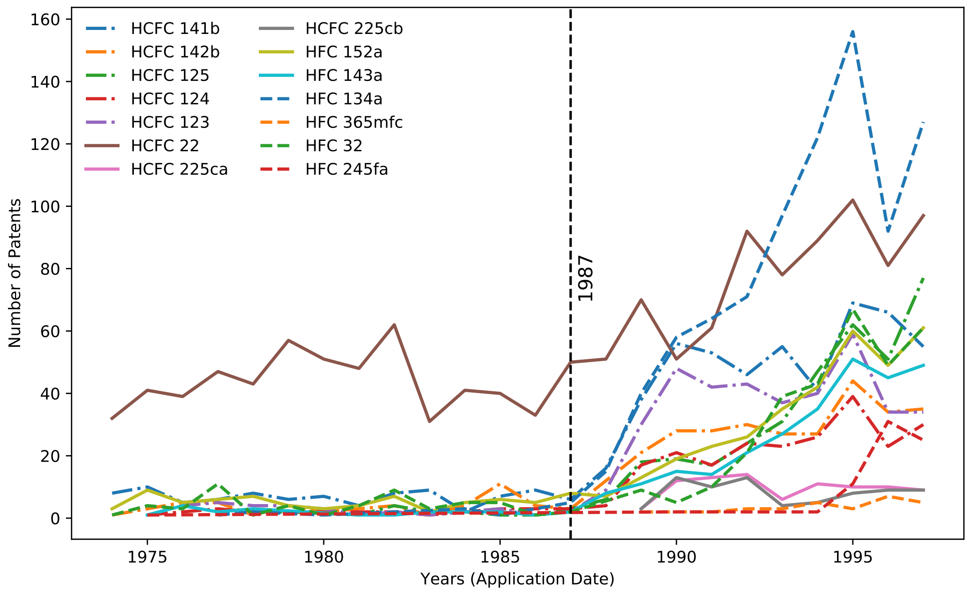
Figure A2: Most frequent codes for patents mentioning CFC susbtitutes before and after 1987

Note: The figure illustrates the differences between the most frequent codes for patents before and after 1987 (year of application is used). The most frequent patent codes before 1987 tend to be the most frequent after 1987. At the same time, some codes with low to zero frequency before 1987 become important after 1987 (e.g., C08G, C10M, C23G or C11D). Only patents with at least 3 molecule occurrences are kept in the sample.

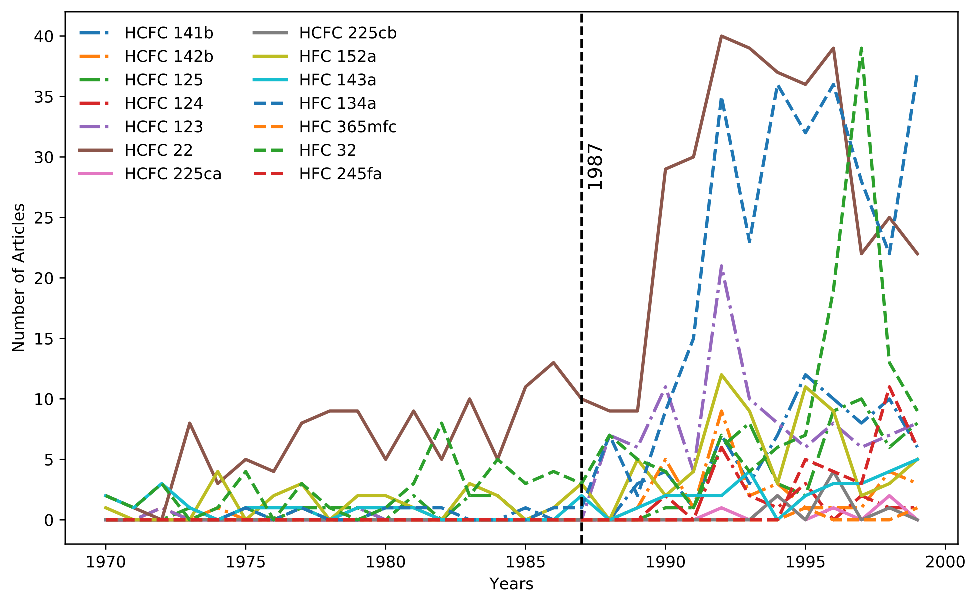
Table A2: List of CFC substitutes

Substitute	PAFT	AFEAS	Substitute for
HCFC-22	No, already marketed, toxicology known	Yes	CFC-11, CFC-12 in foams
HCFC-142b	No, already marketed, toxicology known	Yes	CFC-11, CFC-12 but not ideal
HFC-152a	No, already marketed, toxicology known	Yes	CFC-11, CFC-12 but not ideal
HCFC-123	Yes	Yes	CFC-11 in refrigeration
HFC-134a	Yes	Yes	CFC-12 in refrigeration (car AC)
HCFC-141b	Yes	Yes	CFC-11 in foams
HCFC-124	Yes	Yes	CFC-114 in refrigeration and sterilization
HCFC-125	Yes	Yes	CFC-115 in refrigeration and sterilization
HCFC-225ca	No, second rank candidate	Yes	
HCFC-225cb	No, second rank candidate	Yes	
HFC-32	No, second rank candidate	Yes	refrigeration
HFC-143a	No, second rank candidate	Yes	CFC-12 in refrigeration
HFC-245fa	No	No	CFC-11, HCFC-141b and HCFC-142b in foams
HFC-365mfc	No	No	CFC-11, HCFC-141b and HCFC-142b in foams

Note: The table lists 14 molecules that were considered as potential CFC substitutes in 1988. The columns PAFT and AFEAS indicate whether the molecule was included in the investigations carried out by the PAFT and AFEAS. The PAFT (Program for Alternative Fluorocarbon Toxicity Testing) was created in January 1988 to work on assessing the toxicity of five possible alternatives. The AFEAS (Alternative Fluorocarbon Environmental Acceptability Study), created in December 1988, investigated the atmospheric dynamics of twelve potential CFC substitutes. I use these twelve molecules to form the group of CFC substitutes. I also include in this group two other possible CFC substitutes mentioned in Benedick (2009) and Parson (2003). In the rest of my analysis, I track the evolution of patents and articles mentioning these 14 molecules.



(a) Patents



(b) Articles

Figure A3: Counts in articles and patents for each CFC substitute

Note: These graphs plot the yearly number of articles or patents mentioning the names of given CFC substitutes. We note a clear increase for most CFC substitutes in the 1990s. For patents, the graph shows patents that have been *granted* (as opposed to patent applications) but the years on the x-axis corresponds to the application date. There is on average a two-year delay between patent application and grant.

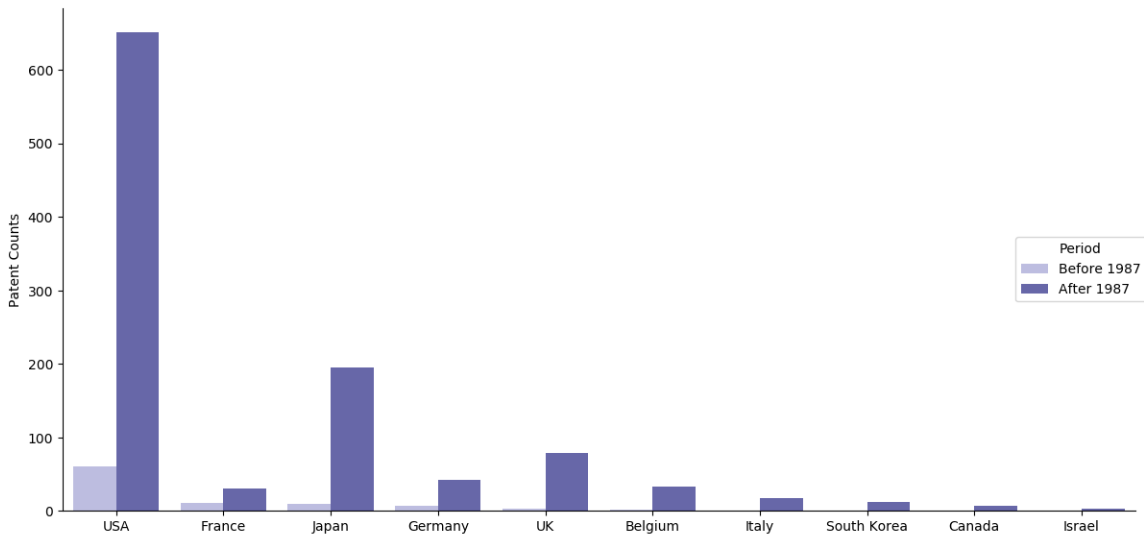


Figure A4: Country of origin of patent assignees before and after 1987.

Note: The figure illustrates that all countries are associated with an increase number of patents mentioning CFC substitutes. We note in particular the strong increase for Japan and the UK. Only patents with at least 3 molecule occurrences are kept in the sample. The year used is the application year. The period "Before 1987" includes the year 1987.

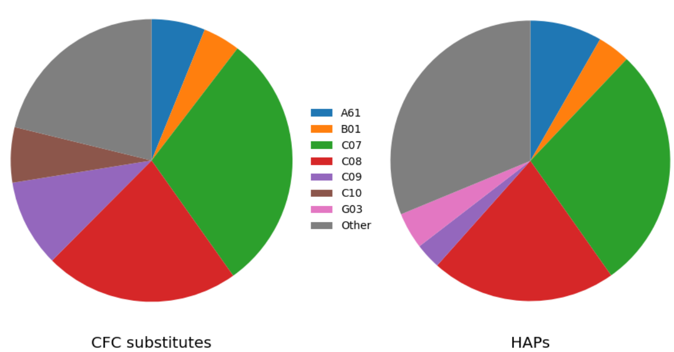


Figure A5: Second-level patent codes

Note: We see that CFC substitutes and HAPs also share similar second-level patent codes.

Table A3: Summary statistics of meta-data

(a) Patents

	CFC Substitutes	HAPs
Education	0.02	0.02
	(0.14)	(0.14)
Company	0.97	0.96
	(0.17)	(0.20)
Government	0.01	0.02
	(0.07)	(0.13)
Facility	0.00	0.00
	(0.07)	(0.02)
Nonprofit	0.00	0.00
	(0.00)	(0.07)
Healthcare	0.00	0.00
	(0.00)	(0.02)
USA	0.61	0.56
	(0.49)	(0.50)
Europe	0.21	0.23
	(0.40)	(0.42)
Japan	0.17	0.17
	(0.37)	(0.38)

(b) Articles

	CFC Substitutes
Citation Count	30.60
	(72.19)
Number of Authors	2.95
	(2.85)
Education	0.75
	(0.43)
Company	0.12
	(0.32)
Government	0.11
	(0.31)
Facility	0.11
	(0.31)
Nonprofit	0.02
	(0.13)
Healthcare	0.02
	(0.15)
USA	0.36
	(0.48)
Europe	0.39
	(0.49)
Japan	0.12
	(0.32)

Note: The tables display summary statistics on the country of origin and types of patent assignees (left-hand side) and on the country and type of affiliation of the authors of articles (right-hand side). Data collection for HAPs in articles is still undergoing due to quota limitation on the Elsevier API. We note that more than 96% of patents are granted to for-profit organizations. The rest is shared among organizations coming from the educational and governmental sector as well as organizations that fit the description of "facility". The majority of patents are granted to assignee domiciliated in the United States. European assignees tend to represent around 20 to 30% of patents; Japanese around 10 to 20%.

For patents, the variables *Education*, *Company*, *Government*, *Facility*, *Nonprofit*, and *Healthcare* are binary variables identifying the type of patent assignee. For articles, "Education" is a dummy variable that equals 1 if at least one of the authors is affiliated with an organization in the higher education sector. "Company" is a dummy variable that equals 1 if at least one of the authors is affiliated with a for-profit private organization. "Government" is a dummy variable that equals 1 if at least one of the authors is affiliated with a governmental entity. "Facility" is a dummy variable that equals 1 if at least one of the authors is affiliated with a facility pursuing research in specialized areas (e.g. nuclear plant, particle accelerators etc...). "Nonprofit" is a dummy variable that equals 1 if at least one of the authors is affiliated with a nonprofit research institute. "Healthcare" is a dummy variable that equals 1 if at least one of the authors is affiliated with an organization where patients are treated. "USA", "Europe" and "Japan" are dummy variables that equal 1 if at least one of the authors is affiliated with, respectively, the USA, a European country and Japan. By European country, I mean any country belonging to the EU in 2016 plus Switzerland, Norway, Serbia, Ukraine, Moldova and Russia. Organization types were collected from the Global Research Identifier Database.

Table A4: Summary statistics for CFC substitutes and HAPs

Variables (pre-1986 average)	Substitutes	HAPs Mean	HAPs Min	HAPs Max	HAPs Std.Dev.
Count	64.2	71.37	41.8	101.8	21.23
Topic 1 (weighted mean)	0.2	0.2	0.16	0.23	0.02
Topic 2 (weighted mean)	0.1	0.11	0.08	0.12	0.01
Topic 3 (weighted mean)	0.43	0.43	0.39	0.47	0.02
Topic 4 (weighted mean)	0.18	0.19	0.15	0.23	0.02
Topic 5 (weighted mean)	0.09	0.08	0.06	0.12	0.02
Topic 1 (unweighted mean)	0.2	0.2	0.17	0.22	0.01
Topic 2 (unweighted mean)	0.1	0.11	0.1	0.12	0.01
Topic 3 (unweighted mean)	0.43	0.43	0.41	0.46	0.01
Topic 4 (unweighted mean)	0.19	0.19	0.17	0.22	0.01
Topic 5 (unweighted mean)	0.09	0.08	0.06	0.1	0.01

Note: The table displays summary statistics for the aggregated CFC substitutes and HAPs for patents. The SCM imposes that the synthetic control's weights be non-negative and sum to 1. This can be problematic in cases where the treated unit lies at the extremes of the distribution of the donor units. We see, here, that the values for CFC substitutes always fall within the range of the values for HAPs. This table confirms that we are not in this case. Hence, there should be no penalty constraining the weights to non-negative and to sum to 1. Note that only HAPs in the small donor pool are used it. Similar results were obtained for articles.

Table A5: Variable weights used in the construction of the synthetic control

	Variable Weight
Topic 1 (weighted mean)	0.04
Topic 2 (weighted mean)	0.04
Topic 3 (weighted mean)	0.02
Topic 4 (weighted mean)	0.03
Topic 5 (weighted mean)	0.02
Log Count	0.86

Note: The table displays the weights assigned to variables in the optimization procedure of the SCM. These weights are for the case of patents with log counts and weighted means of topic proportions, using the small pool of HAPs as donor pool. We note that topic proportions contribute about 15% in constructing the synthetic control.

Table A6: Means over pre-treatment periods for CFC substitutes

	Real S	Synthetic S	Average HAPs
Count (log)	4.17	4.17	4.22
Topic 1 (weighted mean)	0.20	0.20	0.20
Topic 2 (weighted mean)	0.10	0.10	0.11
Topic 3 (weighted mean)	0.43	0.42	0.43
Topic 4 (weighted mean)	0.18	0.19	0.19
Topic 5 (weighted mean)	0.09	0.09	0.08

Note: The table illustrates how the SCM is able to construct a better comparison unit than simply using the mean of many control units. The table displays the mean over the years 1970 to 1985 for log patent counts and topic proportions for the group of CFC substitutes (”Real S”), for the constructed synthetic substitute (”Synthetic S”) and for the average of HAPs. The synthetic control, here, was constructed based on similarity with the variables ”Log Count” and the weighted means of the 5 topic proportions. We see that the synthetic control matches the real substitute group much better than the average of HAPs in terms of log count. This is the core idea motivating the use of the SCM. The HAPs used in calculating the average are only those from the small pool, explaining why the topic proportions are very similar.

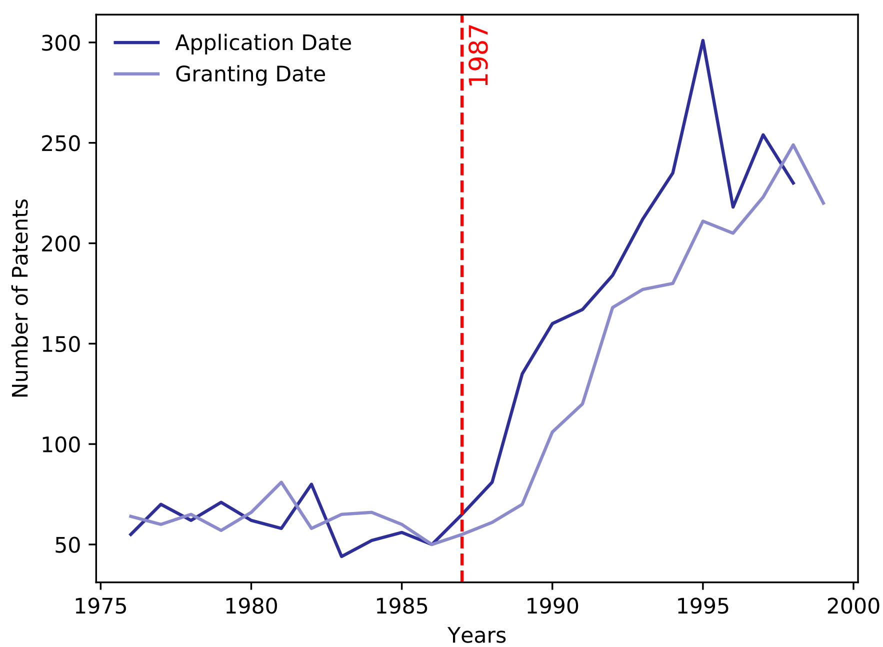


Figure A6: Patent counts with application date vs. grant date for CFC substitutes

Note: The graph plots the number of patents mentioning any CFC subtitutes using the application date of the patent or the granting date. The two curves are very similar, with only about a two-year delay after 1987. Precisely, there is on average a 22-month delay between application and granting, with a standard deviation of 12 months. The graph illustrates that we obtain similar reszults by using the application date for the main analysis.

Table A7: Robustness checks: SCM with counts as outcome variable (instead of log counts)

(a) Patents

Rule	Topic Means	Donor Pool	Pre RMSPE	p-value	ATE	Year
intermediate	unweighted	whole sample	3.35	0.006	71.88	1990
intermediate	unweighted	small pool	3.41	0.000	70.87	1990
intermediate	weighted	small pool	3.70	0.000	72.28	1990
intermediate	weighted	whole sample	3.92	0.000	71.24	1990
weak	weighted	whole sample	8.74	0.000	100.92	1992
weak	unweighted	whole sample	9.68	0.000	84.52	1992
weak	weighted	small pool	10.23	0.000	109.23	1990
weak	unweighted	small pool	10.86	0.000	113.61	1990

(b) Articles

Rule	Topic Means	Donor Pool	Pre RMSPE	p-value	ATE	Year
intermediate	weighted	small pool	1.54	0.000	35.17	1990
intermediate	unweighted	small pool	1.78	0.000	35.52	1990
intermediate	unweighted	whole sample	1.96	0.000	35.04	1992
intermediate	weighted	whole sample	2.03	0.000	35.39	1992
weak	weighted	small pool	2.65	0.000	44.08	1990
weak	unweighted	small pool	2.86	0.000	42.6	1990
weak	weighted	whole sample	4.44	0.006	45.81	1998
weak	unweighted	whole sample	5.65	0.006	46.73	1994

Note: The tables display results for when using counts in levels instead of in log as the outcome variable. The estimated treatment effects for these robustness checks are similar to the effect estimate with the main methodology. "Topic Means" indicates the procedure for aggregating the topic proportions at the molecule level. If "weighted", the calculated proportion of topic j for molecule i is the mean proportion of topic j across all documents mentioning molecule i, weighted by the number of times the molecule appears in the document. "Donor Pool" indicates what sample of HAPs is used in the SCM procedure. For "small pool", the sample of HAPs used corresponds to the twenty HAPs most similar to the treated unit in terms of counts and topic proportions before 1987.

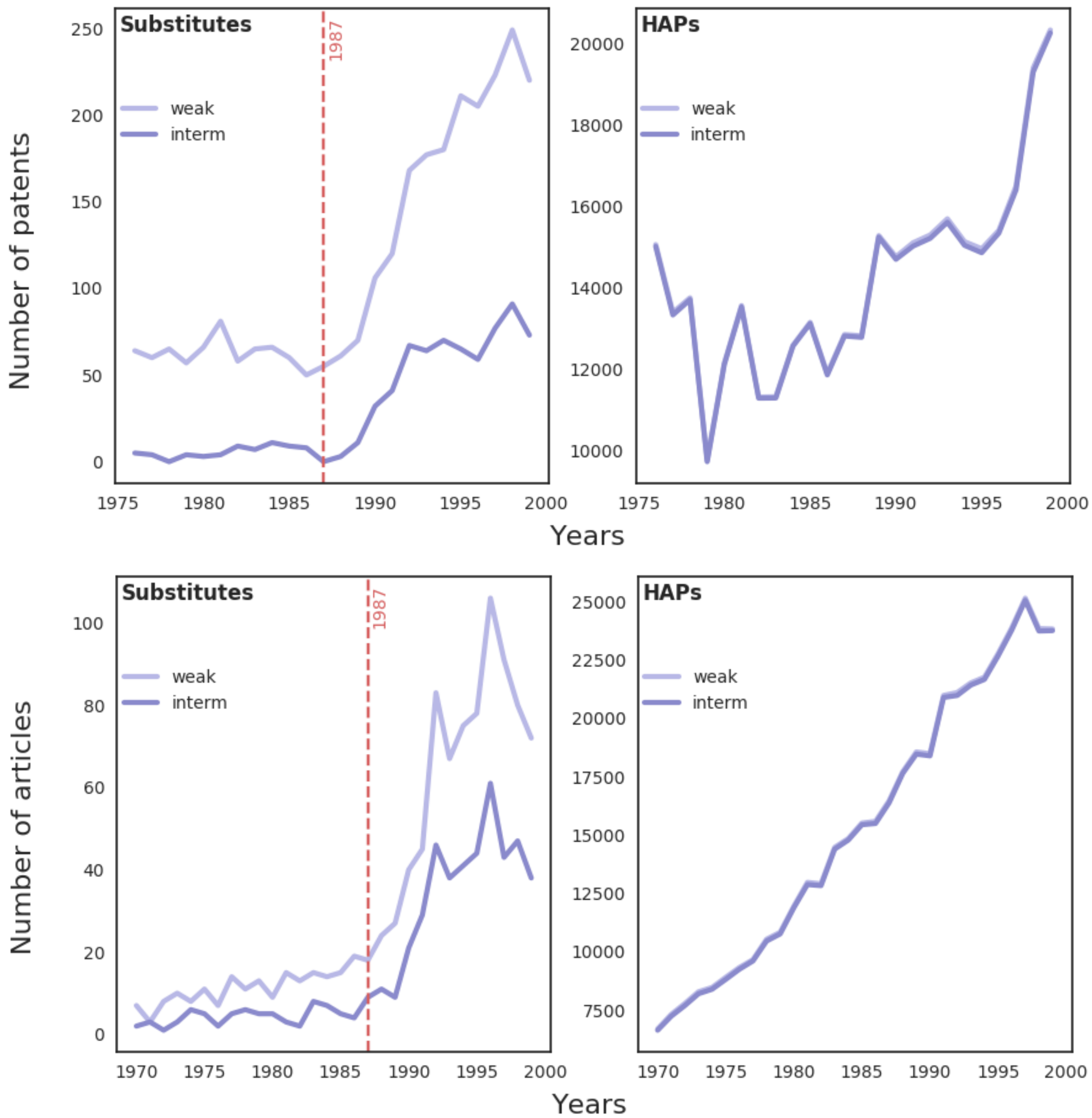


Figure A7: Yearly counts for CFC substitutes and HAPs with different assignment rules for patents and articles.

Note: The figures show the number of patents and articles each year for CFC substitutes and HAPs according to the two different assignment rules. The main results were obtained using the rule called "weak". I test the robustness of these results by using an alternative rule, which I call "intermediate". The intermediate rule is a more conservative way of assigning documents to molecules. When a document mentions several molecules, instead of assigning the document to each molecule, the document is assigned to only the molecule it mentions the most. We note that, as a result, the weak rule has a greater number of documents in the case of CFC substitutes. For HAPs, the graphs show no difference mostly due to the scale of the axis.

Table A8: Robustness check: SCM with alternative assignment rule.

(a) Patents.

Topic Means	Donor Pool	Pre RMSPE	p-value	ATE	Year
unweighted	small pool	0.37	0	1.77	1990
weighted	small pool	0.40	0	2.06	1990
unweighted	whole sample	0.40	–	1.73	1990
weighted	whole sample	0.46	0.03	1.64	1990

(b) Articles.

Topic Means	Donor Pool	Pre RMSPE	p-value	ATE	Year
weighted	small pool	0.27	0.0	1.34	1990
unweighted	small pool	0.28	0.0	1.35	1990
weighted	whole sample	0.28	0.0	1.39	1990
unweighted	whole sample	0.28	0.0	1.31	1990

Note: In this robustness check, I use an alternative rule to assign documents to molecule. The estimated treatment effects for these robustness checks are all higher than the effect estimated with the main methodology. "Topic Means" indicates the procedure for aggregating the topic proportions at the molecule level. If "weighted", the calculated proportion of topic j for molecule i is the mean proportion of topic j across all documents mentioning molecule i, weighted by the number of times the molecule appears in the document. "Donor Pool" indicates what sample of HAPs is used in the SCM procedure. For "small pool", the sample of HAPs used corresponds to the twenty HAPs most similar to the treated unit in terms of counts and topic proportions before 1987.

Table A9: Robustness check: SCM with ten topics.

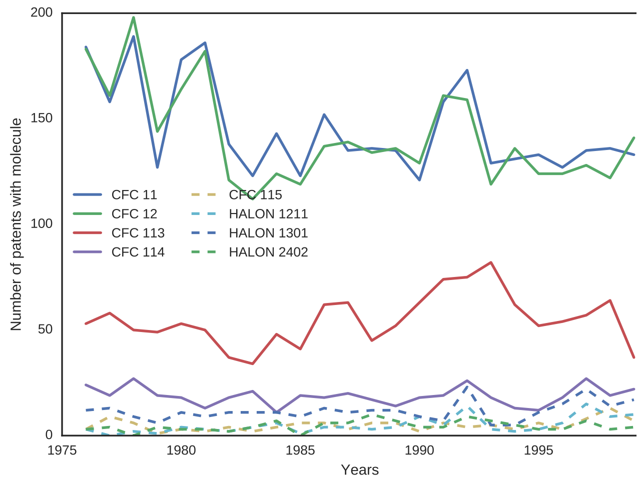
(a) Patents.

Rule	Topic Means	Donor Pool	Pre RMSPE	p-value	ATE	Year
weak	weighted	small pool	0.17	0	1.16	1990
weak	unweighted	small pool	0.17	0	1.17	1990
weak	unweighted	whole sample	0.17	0.035	0.62	1991
weak	weighted	whole sample	0.19	–	0.71	1990
intermediate	unweighted	small pool	0.52	0	2.0	1990
intermediate	unweighted	whole sample	0.52	0.041	1.86	1989
intermediate	weighted	whole sample	0.59	0.053	1.77	1989
intermediate	weighted	small pool	0.67	0	2.01	1990

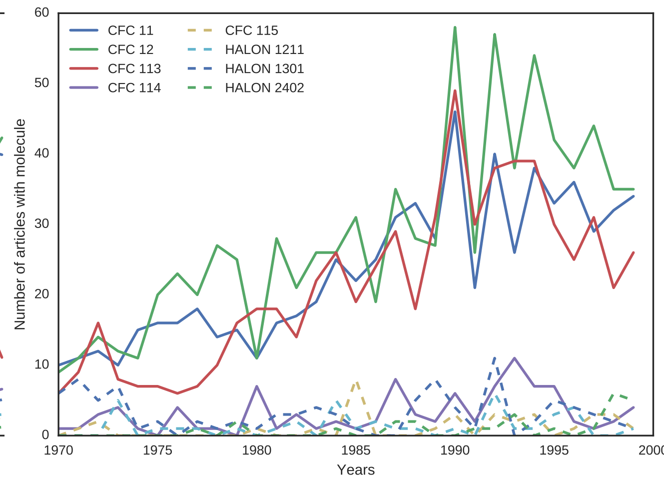
(b) Articles.

Rule	Topic Means	Donor Pool	Pre RMSPE	p-value	ATE	Year
weak	unweighted	whole sample	0.25	0.000	1.01	1990
intermediate	weighted	small pool	0.26	0.000	1.16	1990
weak	weighted	whole sample	0.27	0.018	1.05	1990
intermediate	unweighted	small pool	0.29	0.000	1.25	1990
weak	weighted	small pool	0.30	0.000	1.45	1990
weak	unweighted	small pool	0.32	0.000	1.02	1992
intermediate	weighted	whole sample	0.42	0.000	1.67	1989
intermediate	unweighted	whole sample	0.42	0.000	1.68	1989

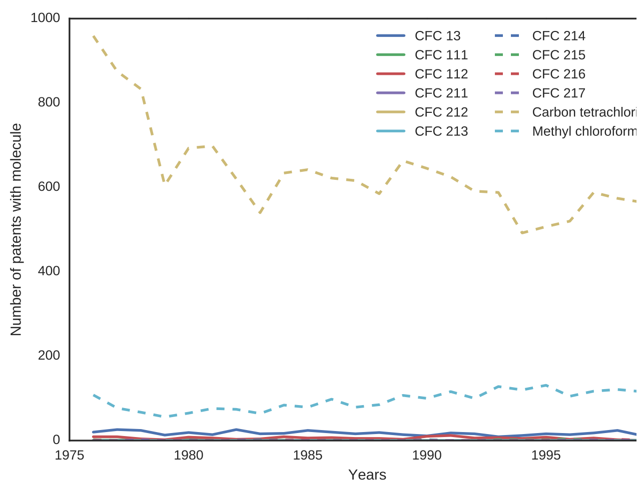
Note: In this robustness check, I increase the number of topics generated by the LDA topic model from five to ten. I, therefore, use ten different topic proportions as covariates in the SCM procedure. "Topic Means" indicates the procedure for aggregating the topic proportions at the molecule level. If "weighted", the calculated proportion of topic j for molecule i is the mean proportion of topic j across all documents mentioning molecule i, weighted by the number of times the molecule appears in the document. "Donor Pool" indicates what sample of HAPs is used in the SCM procedure. For "small pool", the sample of HAPs used corresponds to the twenty HAPs most similar to the treated unit in terms of counts and topic proportions before 1987.



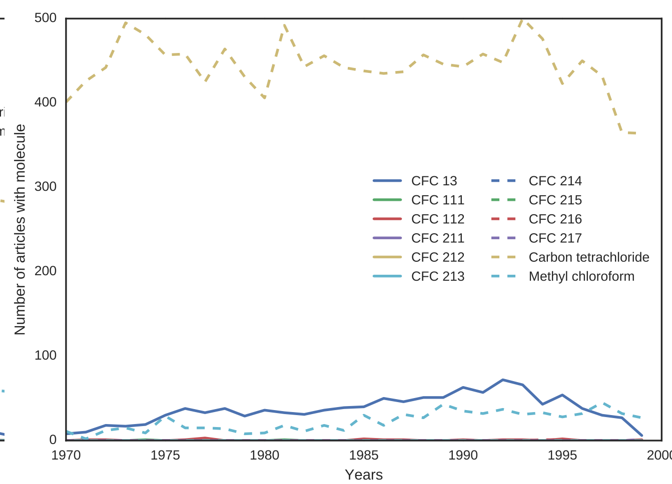
(a) Annex A: Patents



(b) Annex A: Articles



(c) Annex B: Patents



(d) Annex B: Articles

Figure A8: Counts in articles and patents for each molecule of Annex A and Annex B. Note: These graphs plot the yearly number of articles or patents mentioning the names of given molecules included in Annex A and B. We note that most trends are flat, except maybe for Annex A in articles which seem to increase and then decrease.

Table A10: First differences for Annex A and B compounds

(a) Annex A - Patents

	(1)	(2)
Post 1987	0.178^{***}	
	(0.055)	
Post 1987 x Years		-0.009
		(0.017)
Years		0.019^{*}
		(0.011)
Molecule FE	Yes	Yes
R-squared	0.932	0.933
Observations	184	184

Standard errors in parentheses
Dependent variable: Log count of patents
Years are relative to 1987.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Annex A - Articles

	(1)	(2)
Post 1987	0.526^{***}	
	(0.070)	
Post 1987 x Years		-0.008
		(0.017)
Years		0.034^{***}
		(0.008)
Molecule FE	Yes	Yes
R-squared	0.838	0.843
Observations	240	240

Standard errors in parentheses
Dependent variable: Log count of articles
Years are relative to 1987.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(c) Annex B - Patents

	(1)	(2)
Post 1990	0.175^{***}	
	(0.058)	
Post 1990 x Years		0.020
		(0.018)
Years		0.001
		(0.007)
Molecule FE	Yes	Yes
R-squared		
Observations	.971	.97
N	207	207

Standard errors in parentheses
Dependent variable: Log count of patents
Years are relative to 1990.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(d) Annex B - Articles

	(1)	(2)
Post 1990	0.152^{***}	
	(0.056)	
Post 1990 x Years		-0.040^{**}
		(0.017)
Years		0.022^{***}
		(0.005)
Molecule FE	Yes	Yes
R-squared		
Observations	.975	.977
N	210	210

Standard errors in parentheses
Dependent variable: Log count of articles
Years are relative to 1990.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The regressions indicate statistically significant mean shift between before and after 1987, except for Annex B in patents; however these are small in magnitude.

Table A11: Difference-in-differences for Annex A and B compounds.

(a) Annex A - Patents

	(1)	(2)
Post 1987 x Annex A	0.024	
	(0.055)	
Post 1987 x Annex A x Years		-0.009
		(0.017)
Annex A x Years		0.005
		(0.011)
Years		0.014^{***}
		(0.001)
Year FE	Yes	No
Molecule FE	Yes	Yes
R-squared	0.987	0.985
Observations	736	736

Standard errors in parentheses
Dependent variable: Log count of patents
Years are relative to 1987.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Annex A - Articles

	(1)	(2)
Post 1987 x Annex A	0.069	
	(0.073)	
Post 1987 x Annex A x Years		-0.008
		(0.017)
Annex A x Years		0.006
		(0.008)
Years		0.028^{***}
		(0.002)
Year FE	Yes	No
Molecule FE	Yes	Yes
R-squared	0.966	0.964
Observations	960	960

Standard errors in parentheses
Dependent variable: Log count of articles
Years are relative to 1987.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(c) Annex B - Patents

	(1)	(2)
Post 1990 x Annex B	0.080	
	(0.063)	
Post 1990 x Annex B x Years		0.020
		(0.018)
Annex B x Years		-0.004
		(0.007)
Years		0.005^{***}
		(0.002)
Year FE	Yes	No
Molecule FE	Yes	Yes
R-squared		
Observations	.988	.987
N	828	828

Standard errors in parentheses
Dependent variable: Log count of patents
Years are relative to 1990.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(d) Annex B - Articles

	(1)	(2)
Post 1990 x Annex B	-0.251^{***}	
	(0.065)	
Post 1990 x Annex B x Years		-0.040^{**}
		(0.017)
Annex B x Years		-0.004
		(0.005)
Years		0.026^{***}
		(0.002)
Year FE	Yes	No
Molecule FE	Yes	Yes
R-squared		
Observations	.968	.967
N	840	840

Standard errors in parentheses
Dependent variable: Log count of articles
Years are relative to 1990.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The difference-in-differences specifications indicate that a positive and statistically significant treatment effect for Annex in patents and a negative one for Annex B in articles. The magnitudes however are small.

Table A12: SCM for Annex A and B compounds

(a) Annex A - Patents

Topic Means	Donor Pool	Pre RMSPE	p-value	ATE	Year
unweighted	whole sample	0.08	0.06	-0.01	–
weighted	whole sample	0.09	0.14	-0.0	–
unweighted	small pool	0.13	0.90	-0.09	–
weighted	small pool	0.14	0.60	-0.03	–

(b) Annex A - Articles

Topic Means	Donor Pool	Pre RMSPE	p-value	ATE	Year
unweighted	small pool	0.15	0.250	-0.12	–
unweighted	whole sample	0.15	0.471	0.08	–
weighted	whole sample	0.16	0.296	0.18	–
weighted	small pool	0.25	0.400	0.33	1990

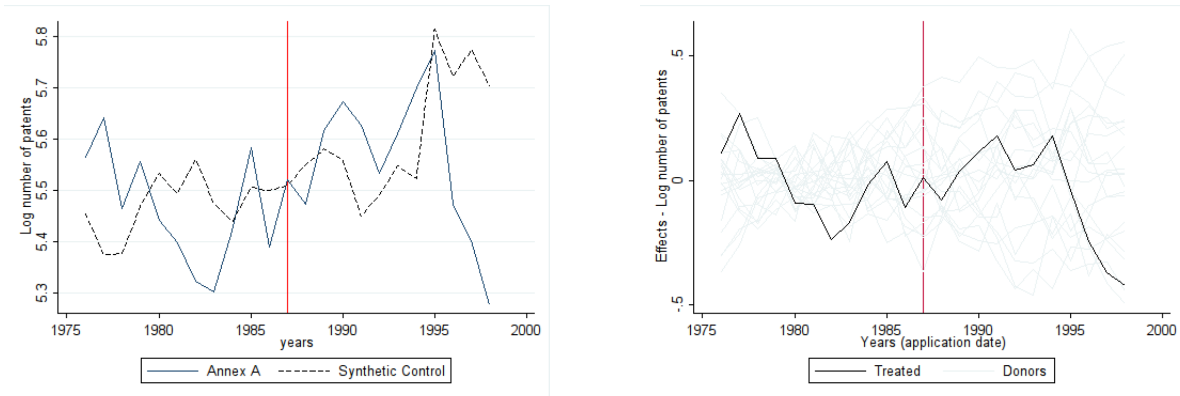
(c) Annex B - Patents

Topic Means	Donor Pool	Pre RMSPE	p-value	ATE	Year
weighted	whole sample	0.07	0.09	-0.18	–
unweighted	whole sample	0.07	0.10	-0.16	–
unweighted	small pool	0.09	0.20	-0.23	–
weighted	small pool	0.12	0.30	-0.28	–

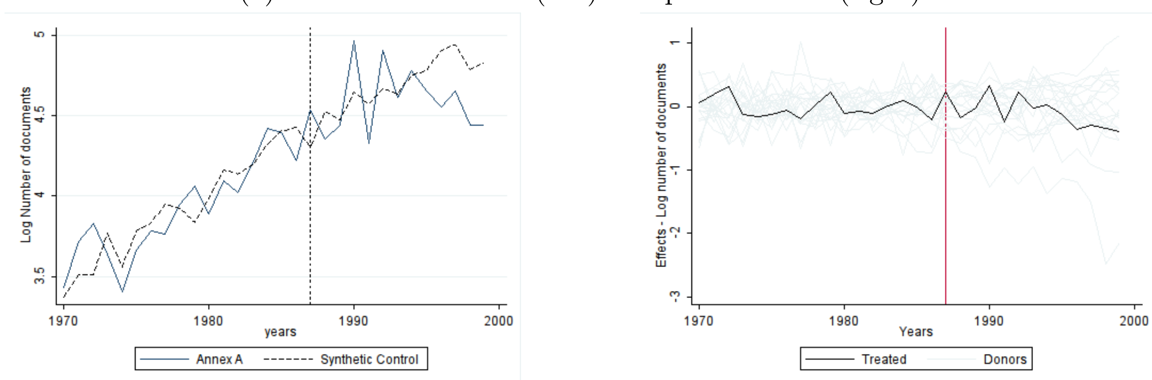
(d) Annex B - Articles

Topic Means	Donor Pool	Pre RMSPE	p-value	ATE	Year
unweighted	whole sample	0.15	0.036	-0.32	–
weighted	whole sample	0.16	0.112	-0.28	–
weighted	small pool	0.38	0.200	-0.86	–
unweighted	small pool	0.40	0.300	-0.86	–

Note: All tables refer to SCM implementation using log count as outcome variable and using the weak rule of assigning documents. Almost none of the procedures yield treatment effects that are statistically significant. Most p-values are greater than 0.10. These results indicate that Montreal did not trigger a large decrease nor a large increase in the number of patetns and articles mentioning Annex A and B compounds. "Topic Means" indicates the procedure for aggregating the topic proportions at the molecule level. If "weighted", the calculated proportion of topic j for molecule i is the mean proportion of topic j across all documents mentioning molecule i, weighted by the number of times the molecule appears in the document. "Donor Pool" indicates what sample of HAPs is used in the SCM procedure. For "small pool", the sample of HAPs used corresponds to the twenty HAPs most similar to the treated unit in terms of counts and topic proportions before 1987.



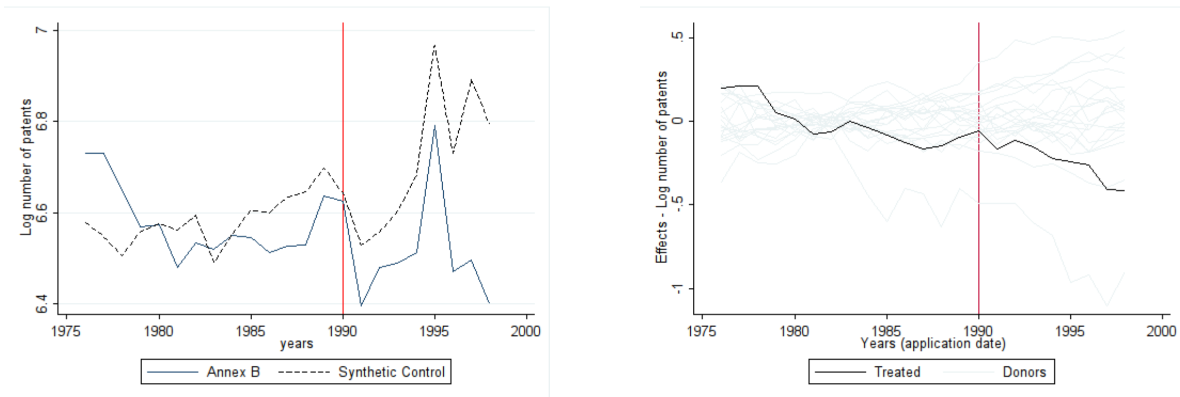
(a) Patents: raw effect (left) and placebo tests (right)



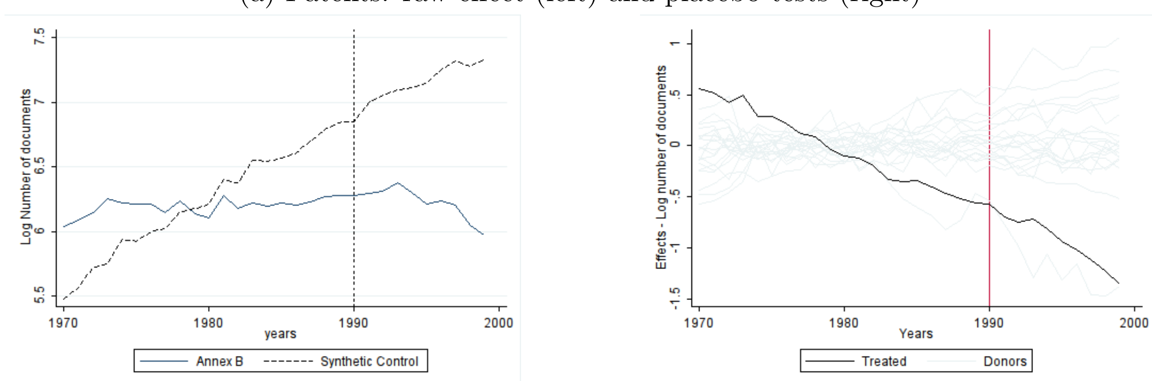
(b) Articles: raw effect (left) and placebo tests (right)

Figure A9: SCM for Annex A compounds

Note: Figures A9a and A9b display the results of the synthetic control method for Annex A compounds for patents and articles. There is no significant increase or decrease in the number of patents and articles mentioning Annex A compounds. In all cases, the method is implemented using the topic proportions of a LDA model with 5 topics and the weak rule for assigning documents to molecule groups. Weighted means of topic proportions are used for patent and unweighted means for articles because these are the specifications that yielded lowest pre-RMPSE. The graphs on the left-hand side represent the raw effect, that is the observed time series of the treated group along with the time series of the constructed control. On the right-hand sides are shown the placebo tests, the non-parametric tests to evaluate the significance of the results; black lines show the effect on the treated group relative to the control group, while each gray line is a placebo test performed on an unit drawn from the donor pool.



(a) Patents: raw effect (left) and placebo tests (right)



(b) Articles: raw effect (left) and placebo tests (right)

Figure A10: SCM for Annex B compounds

Note: Figures A10a and A10b display the results of the synthetic control method for Annex B compounds for articles and patents. We note that in this case the synthetic control offers a poor fit to the observed data. Hence we cannot infer whether there is anincrease or a decrease. In all cases, the method is implemented using the topic proportions of a LDA model with 5 topics and the weak rule for assigning documents to molecule groups. Weighted means of topic proportions are used for patent and unweighted means for articles because these are the specifications that yielded lowest pre-RMPSE. The graphs on the left-hand side represent the raw effect, that is the observed time series of the treated group along with the time series of the constructed control. On the right-hand sides are shown the placebo tests, the non-parametric tests to evaluate the significance of the results; black lines show the effect on the treated group relative to the control group, while each gray line is a placebo test performed on an unit drawn from the donor pool.

Appendix to Chapter 2

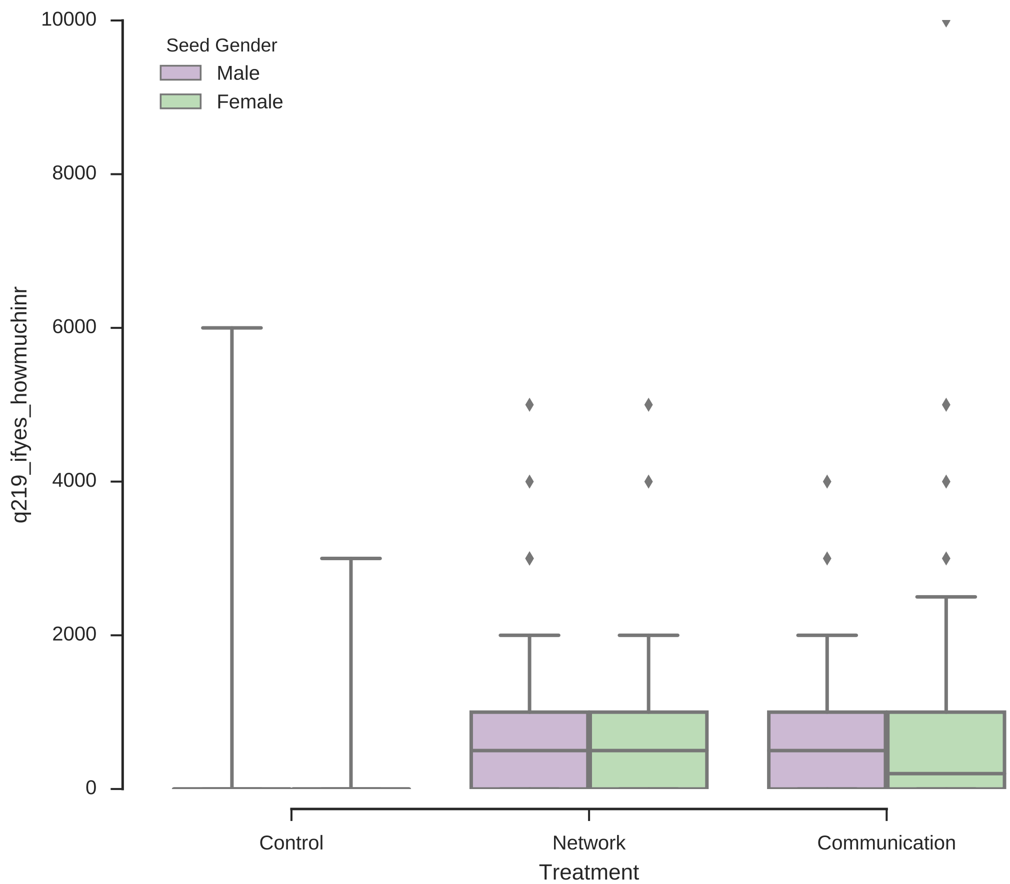


Figure B1: Boxplot plot of amount of savings in Rupees per treatment group.

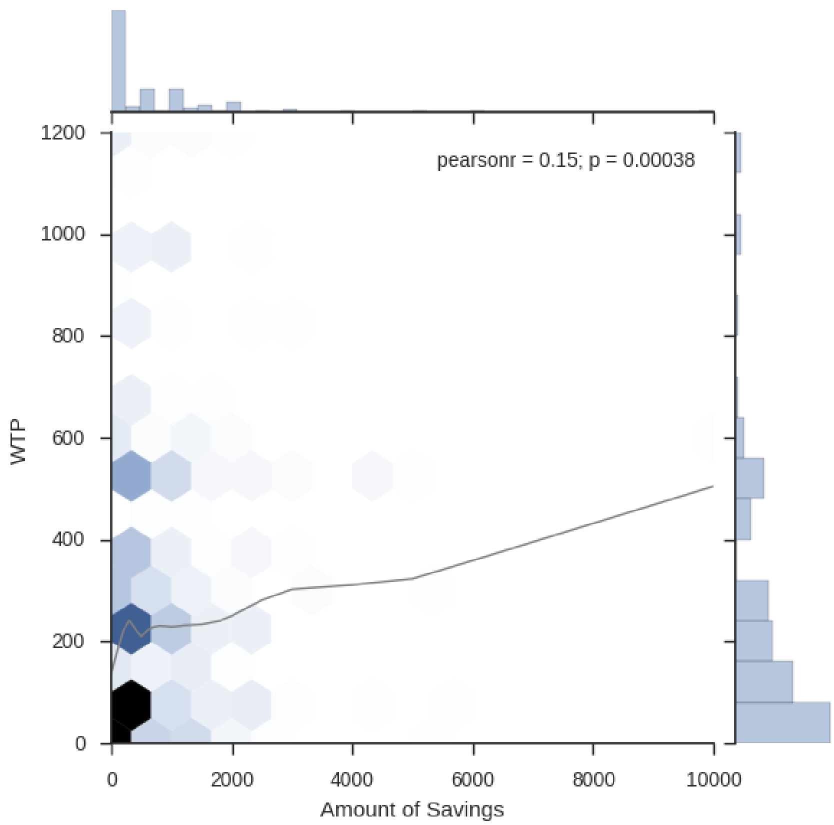


Figure B2: Hexabin plot of WTP and amount of savings in Rupees.

Question	**Answer type**	**Label used in table**
Have you seen a solar lantern before?	Yes or no.	Seen lantern before
Do you know someone with a solar lantern?	Yes or no.	Know someone with lantern
Do you think a solar lantern can function properly without many maintenance problems?	Yes or no.	Can function
How much would you say this solar lantern costs?	Amount in Rupees.	Cost estimate
Do you think that the solar lantern is an innovative product?	Definitely not, Not really, Neutral, Somewhat, Definitely.	Innovative product
Would you say that a solar lantern is a superior product compared to a kerosene lamp?	Definitely not, Not really, Neutral, Somewhat, Definitely.	Superior to kerosene lamps
Do you think you will recommend others to use a solar lantern instead of a kerosene lamp?	Definitely not, Not really, Neutral, Somewhat, Definitely.	Will recommend to others
Would you feel safer if there was more light?	Definitely not, Not really, Neutral, Somewhat, Definitely.	Would feel safer if more light
Have you ever been victim of a kerosene fire?	Yes = 1, No = 0	Was victim of kerosene fire
Do you know someone who has been victim of a kerosene fire?	Yes = 1, No = 0	Knows a victim of a kerosene fire

Table B1: Description of questions used in Table 2.10.

Question	Answer type	Label used in table
Do your children use lighting for studying	Yes or No.	Children use lighting for studying
Do you believe your current lighting solution is bad for your eyesight?	Definitely not = 1, Not really = 2, Neutral = 3, Somewhat = 4, Definitely = 5.	Current lighting bad for eyesight
Who in your household do you think will/would mostly be using the solar lantern?	Myself, My spouse, My children, No one, Others	Mostly be using: myself and Mostly be using: my spouse
Do you and your spouse talk about what to spend money on?	Never = 0, Sometimes = 1, Often = 2	Talk about how to spend money
Do you think more women should work outside of the household or own a business?	Definitely not = 1, Not really = 2, Neutral = 3, Somewhat = 4, Definitely = 5	More women should work outside
How often did you participate in village meetings during the past six months?	Almost all of them = 2, Some of them = 1, None of them = 0	Participation in village meetings
How often did you participate in farmers' cooperative meetings during the past six months?	Almost all of them = 2, Some of them = 1, None of them = 0	Participation in farmers' cooperative meetings
How often did you participate in religious group events during the past six months?	Almost all of them = 2, Some of them = 1, None of them = 0	Participation in religious group events
How often did you participate in political events during the past six months?	Almost all of them = 2, Some of them = 1, None of them = 0	Participation in political events
Do you trust other villagers?	Definitely not = 1, Not really = 2, Neutral = 3, Somewhat = 4, Definitely = 5	Trust other villagers
In your spare time, do you mostly spend time with your friends or stay home?	Spend time with friends = 1, Stay home = 0	Spend time with friends (dummy)
How many friends do you have in this village?	number of friends	Number of friends

Table B2: Description of questions used it Table 2.12 and 2.13.

Appendix to Chapter 3

Proofs

We first establish two intermediate results, Remark C.1 and C.2 below, which will be useful to establish other results.

Remark C.1. $\forall \hat{z}_j, \quad \frac{dp_j^*(\hat{z}_j)}{d\hat{z}_j}|_{\hat{z}_{-j}} \geq 0$

Proof.

$$\begin{aligned}
\frac{d\Pi_{P_j}}{dp_j} = 0 &\Leftrightarrow s_jQ_j + (s_jp_j - c)\frac{\partial Q_j}{\partial p_j} = 0 \\
&\Leftrightarrow s_jQ_j + (s_jp_j - c)\frac{1}{\mu}Q_j(\frac{Q_j}{M} - 1) = 0 \\
&\Leftrightarrow \frac{\mu}{1 - \frac{Q_j}{M}} + \frac{c}{s_j} - p_j = F(p_j, \hat{z}_j, p_{-j}, \hat{z}_{-j}) = 0
\end{aligned}$$

In turn, by the implicit function theorem:

$$\begin{aligned}
\frac{dp_j^*}{d\hat{z}_j} &= -\frac{\frac{\partial F}{\partial \hat{z}_j}}{\frac{\partial F}{\partial p_j}} = -\frac{\frac{\mu}{M}\frac{1}{(1-\frac{Q_j}{M})^2}\frac{\partial Q_j}{\partial \hat{z}_j}}{-1 + \frac{\mu}{M}\frac{1}{(1-\frac{Q_j}{M})^2}\frac{\partial Q_j}{\partial p_j}} = \frac{\frac{\partial Q_j}{\partial \hat{z}_j}}{\frac{M}{\mu}(1 - \frac{Q_j}{M})^2 - \frac{\partial Q_j}{\partial p_j}} \\
&= \frac{\frac{\beta}{\mu}Q_j(1 - \frac{Q_j}{M})}{\frac{M}{\mu}(1 - \frac{Q_j}{M})^2 + \frac{1}{\mu}Q_j(1 - \frac{Q_j}{M})} = \frac{\beta Q_j}{M - Q_j + Q_j} = \frac{\beta}{M}Q_j > 0 \qquad \text{(C.1)}
\end{aligned}$$

□

Remark C.2. $\forall \hat{z}_j, \quad \frac{dQ_j}{d\hat{z}_j}|_{\hat{z}_{-j}} > 0$

Proof. Total derivative of demand:

$$\frac{dQ_j}{d\hat{z}_j} = \frac{\partial Q_j}{\partial \hat{z}_j} + \frac{\partial Q_j}{\partial p_j}\frac{dp_j^*}{d\hat{z}_j} + \sum_{-j}\frac{\partial Q_j}{\partial p_{-j}}\frac{dp_{-j}^*}{d\hat{z}_j}$$

This gives, if $\mu = 1$:

$$\frac{dQ_j}{d\hat{z}_j} = \beta Q_j\big(1 - \frac{Q_j}{M}\big) + \frac{1}{\mu}Q_j\big(\frac{Q_j}{M} - 1\big)\frac{\beta}{M}Q_j - \sum_{-j}\frac{1}{M\mu}Q_jQ_{-j}\frac{\beta Q_jQ_{-j}}{M^2(1 - \frac{Q_{-j}}{M})}$$

Simplifying:

$$\frac{dQ_j}{d\hat{z}_j} = \beta Q_j(1 - \frac{Q_j}{M})^2 - \sum_{-j}\frac{1}{M^3}(Q_jQ_{-j})^2\frac{\beta}{(1 - \frac{Q_{-j}}{M})}$$

Since $M - Q_j \geq Q_{-j}$, we have:

$$\frac{dQ_j}{d\hat{z}_j} \geq \beta \frac{Q_j}{M^2} Q_{-j}^2 - \frac{1}{M^2}(Q_j Q_{-j})^2 \frac{\beta}{(M - Q_{-j})}$$
$$= \frac{\beta}{M^2} Q_j Q_{-j}^2 (\frac{M - Q_{-j} - Q_j}{M - Q_{-j}}) \geq 0$$

□

Proof of Remark 1

Proof. Consider the stage 2 profit function (induced by the equilibrium prices):

$$\Pi^*_{P_j}(z_j, z_{-j}) = \big(s_j p^*_j(z_j, z_{-j}) - c_j\big) Q^*_j(z_j, z_{-j}) - R_0 - R_P z_j \tag{C.2}$$

At equilibrium we have: $p^*_j = \frac{c_j}{s_j} + \frac{\mu}{1 - Q^*_j/M} \Leftrightarrow Q^*_j = M\big(1 - \frac{s_j \mu}{s_j p^*_j - c}\big)$
Hence, we can rewrite Eq. C.2 as:

$$\Pi^*_{P_j}(z_j, z_{-j}) = M\big(s_j p^*_j(z_j, z_{-j}) - c_j - \mu s_j\big) - R_0 - R_P z_j$$

Taking the derivative with respect to z_j and knowing that $\frac{dp^*_j}{d\hat{z}_j} = \frac{\beta}{M} Q_j > 0$ from Eq. C.1 (proof of Remark C.1):

$$\frac{d\Pi^*_{P_j}(z_j, z_{-j})}{dz_j} = M s_j \frac{dp_j}{dz_j} - R_P = \beta s_j Q_j - R_P. \tag{C.3}$$

We know that Q_j monotonically increases with $\hat{z}_j$ (Remark C.2). Q_j therefore takes values between a minimum, call it Q^0_j, when $z_j = 0$, and up to M when z_j goes to infinity[18]. If $\beta s_j M < R_P$, then $\frac{d\Pi^*_{P_j}(z_j, z_{-j})}{dz_j}$ is always negative and the highest possible profits will always be for $z_j = 0$: there is no incentives for more radical innovation. On the contrary, if $R_P < \beta s_j Q^0_j$, $\frac{d\Pi^*_{P_j}(z_j, z_{-j})}{dz_j}$ is always positive and highest profits are reached for $z_j = 1$. In the last case, when $\beta s_j Q^0_j < R_P < \beta s_j M$, there exists a value $\tilde{z}_j(z_{-j}) > 0$ above which $\frac{d\Pi^*_{P_j}(z_j, z_{-j})}{dz_j}$ is positive, meaning profits increase monotonically. This remark the profit function of each producer increases monotonically with z_j beyond some threshold value $\tilde{z}_j$, and becomes higher than the value at $z_j = 0$ after another threshold $\underline{z}_j$. This threshold value $\underline{z}_j$ does in fact depend on z_{-j} the innovation level of the other player. We can therefore define the function $\underline{z}_1(z_2)$ denoting the minimum level of innovation for firm 1 so that profits become larger than under $z_1 = 0$, given z_2 the value chosen by firm 2. In the same way, we can define $\underline{z}_2(z_1)$. Thus, either $\underline{z}_j(z_{-j}) \in [0, 1]$, or $\Pi^*_{P_j}(z_j, z_{-j}) < \Pi^*_{P_j}(0, z_{-j})$ for $z_j \in [0, 1]$. □

[18] There will be a different Q^0_j for every z_{-j}. The smallest Q^0_j will be for $z_{-j} = 1$

Proof of Remark 2

Proof. By Remark 1, we know that if $\underline{z}_j(z_{-j}) < 1$, then the best response of firm j to the value z_{-j} is the maximum value $z_j = 1$. On the contrary, if $\underline{z}_j(z_{-j}) > 1$, then the best response of firm j to the value z_{-j} is 0.
In the first case above, $\boldsymbol{\imath}^U > (1,1)$ implies that $\underline{z}_1(z_2) < 1$ for all z_2, including for $z_2 = 1$, and $\underline{z}_2(z_1) < 1$ including for $z_1 = 1$. Hence, the best response of firm 1 is $z_1 = 1$ and similarly for firm 2, yielding the Nash Equilibrium $(1,1)$.
In the second case above, if $\boldsymbol{\imath}^U < (1,1)$ or if $\asymp^U$ does not exist, this means that $\underline{z}_2(1) > 1$ so the best response of firm 1 to $z_2 = 1$ is $z_1 = 0$. The same is true for firm 2, yielding two equilibria $(0,1)$ and $(1,0)$. □

Proof of Remark 3

Proof. Consider the profit function of the supplier if the supplier could ensure that the producers choose the same level of innovation z_i. Denote it $\Pi_i^S(z_i)$ (is that compatible with other notation choices?). Both producers produce the same quantity at the same price determined by level of innovation z_i. We denote them respectively $Q^*(z_i)$ and $p^*(z_i)$. Also denote $C^c(z_i)$ the cost under successful coordination and $C^m(z_i)$ the cost under unsuccessful coordination. The derivative of $\Pi_i^S(z_i)$ with respect to z_i is:

$$\frac{dE[\Pi_i^S]}{dz_i} = \frac{dp^*}{dz_i}Q(z_i) + p^*\frac{dQ^*}{dz_i} - R_s - \theta\frac{dC^c}{dQ}\frac{dQ^*}{dz_i} - (1-\theta)(\frac{\partial C^m}{\partial Q}\frac{dQ^*}{dz_i} + \frac{\partial C^m}{\partial \rho}\frac{d\rho}{dz_i}) \tag{C.4}$$

Since we have a finite market of size M, there is a point at which the market becomes saturated, i.e. an increase in the level of innovation of the products does not lead to more demand. Hence, in the symmetric case, both $p^*(z_i)$ and $Q^*(z_i)$ reach a plateau for some value of z_i . The derivative in equation C.4 becomes $-R_s + (1-\theta)\sigma\partial C^m/\partial\rho$, which is negative. Thus, if the cost and demand parameters are such that there is a value of z_i at which profits are maximized and positive, then there is a larger value of z_i at which point profits fall under $\Pi_i^S(0)$. Denote it $\bar{z}_i$. Additionally, since at $z_i = 0$, profits originally fall with increasing z_i, there is also a value $\underline{z}_i$ under which profits are less than $\Pi_i^S(0)$.

Hence either there exists $\underline{z}_i$ and $\bar{z}_i$ such that $0 < \underline{z}_i < z_i^* < \bar{z}_i$, or $E[\Pi_i^S(z_i)] < \Pi^S(0)$ for all $z_i \in (0,1]$. Given this, the possible NE follow from 2. Indeed, if $z_i^* \geq \underline{z}_j(z_i^*)$, then producers will be willing to invest z_i^* as well. If on the other hand $z_i^* < \underline{z}_j(z_i^*)$, then the supplier has to instead the first possible value of z_i such that $z_i = \underline{z}_j(z_i)$ (which is the same value for both producers since we are in the symmetric case). Call this value z_i^c. $z_i = z_i^c$ ensures that producers will innovate too (each choosing z_i^c by Remark 2). This is only beneficial to the supplier if $z_i^c < \bar{z}_i$. Finally, if instead $\bar{z}_i < z_i^c$, or if we are in the case in which $E[\Pi_i^S(z_i)] < \Pi^S(0)$ for all $z_i \in (0,1]$, then there will be no innovative investments. □

Proof of Result 1

Proof. We first show that the maximizer z_i^* that arises in the equilibrium (z_i^*, z_i^*, z_i^*) decreases with θ. Then we will show that as θ increases, the equilibrium can shift to $(0,0,0)$.
By the envelope theorem, $\frac{dz_i^*}{d\theta} = \frac{\partial^2 E[\Pi^S]/\partial\theta\partial z_i}{-\partial^2 E[\Pi]^S/\partial z_i\partial z_i}$, where the derivatives are estimated at z_i^*.

Since at z_i^* the denominator is positive, the sign is determined by the sign of the cross-derivative.
Since we are in the symmetric case, both producers produce the same quantity at the same price determined by level of innovation z_i (Remark 3) so denote them $Q^*(z_i)$ and $p^*(z_i)$. Also denote $C^c(z_i)$ the cost under successful coordination and $C^m(z_i)$ the cost under unsuccessful coordination.

$$\frac{\partial E[\Pi^S]}{\partial z_i} = \frac{\partial p^*}{\partial z_i}Q(z_i) + p^*\frac{\partial Q^*}{\partial z_i} - R_s - (1-\theta)\frac{\partial C^c}{\partial Q}\frac{\partial Q^*}{\partial z_i} - \theta(\frac{\partial C^m}{\partial Q}\frac{\partial Q^*}{\partial z_i} + \frac{\partial C^m}{\partial \rho}\frac{d\rho}{dz_i})$$

$$\Rightarrow \frac{\partial^2 E[\Pi^S]}{\partial\theta\partial z_i} = \underbrace{\frac{\partial Q^*}{\partial z_i}}_{\geq 0}\underbrace{(\frac{\partial C^m}{\partial Q} - \frac{\partial C^c}{\partial Q})}_{>0} + \underbrace{\frac{\partial C^m}{\partial \rho}}_{<0}\underbrace{\frac{\partial \rho}{\partial z_i}}_{<0} > 0 \tag{C.5}$$

The sign of each term is evident except for $\frac{\partial C^m}{\partial Q} - \frac{\partial C^c}{\partial Q}$, which is positive because $\frac{\partial C^m}{\partial Q} - \frac{\partial C^c}{\partial Q} = (2^{k/(1-\sigma z_i^*)} - 2^k)kQ^{k-1} > 0$.
Within the region in which the (z_i^*, z_i^*, z_i^*) solution holds ($z_i^* \geq \underline{z}_j$ and $E\Pi(z_i^*) > \Pi(0)$), we therefore have that z_i^* increases with θ. But θ also changes the size of that region. First, since z_i^* decreases as the chance of miscoordination increases, it could fall under $\underline{z}_j$ (which does not vary with θ, switching the NE to, at best, $\underline{z}_j, \underline{z}_j, \underline{z}_j$). Second, by the envelope theorem, $\frac{dE\Pi(z_i^*,\theta)}{d\theta} = \frac{\partial E\Pi(z_i^*(\theta),\theta)}{\partial\theta}$. This is $-C^c(z_i^*) + C^m(z_i^*) > 0$ since costs under miscoordination are higher than under coordination. Hence, the profits decrease as the chance of miscoordination increases. In particular, the profits can drop under $\Pi_i(0)$, switching the NE to $(0,0,0)$. These possible discrete changes in the NE lead to the same conclusion that an increase in the chance of miscoordination decreases the equilibrium value of the innovation. □

Proof of Result 2

Proof.

$$\frac{d^2 z_S^*}{dkd\theta} \propto \underbrace{\frac{d}{dk}(\frac{\partial^2 E[\Pi_S]}{\partial\theta\partial z_S})}_{\mathcal{A}}\underbrace{(-\frac{\partial^2 E[\Pi_S]}{\partial z_S\partial z_S})}_{>0} + \underbrace{\frac{\partial^2 E[\Pi_S]}{\partial\theta\partial z_S}}_{<0}\underbrace{\frac{d}{dk}(\frac{\partial^2 E[\Pi_S]}{\partial z_S\partial z_S})}_{\mathcal{B}}$$

Consider the term $\mathcal{A}$ first, for which we use Eq. C.5:

$$\mathcal{A} = \underbrace{\frac{dQ^*}{dz_S}}_{>0}\underbrace{\frac{d}{dk}(\frac{dC^c}{dQ} - \frac{dC^m}{dQ})}_{A} - \underbrace{\frac{d\rho}{dz_S}}_{<0}\underbrace{\frac{d}{dk}(\frac{dC^m}{d\rho})}_{B}$$

$$\frac{d}{dk}A = Q^{-1+k}(2^k - 2^{k/(1-z\sigma)} + k(2^k + \frac{2^{k/1-z\sigma}}{-1+z\sigma}log(2)) + (2^k - 2^{k/(1-z\sigma)})klog(Q)) < 0$$

$$\frac{d}{dk}B = (-log(2))\frac{2^{k/\rho}Q^k(\rho + klog(2) + klogQ^\rho)}{\rho^3} < 0$$

$$\Rightarrow \mathcal{A} = \underbrace{\frac{dQ^*}{dz_S}}_{>0}\underbrace{\frac{d}{dk}(\frac{dC^c}{dQ} - \frac{dC^m}{dQ})}_{<0} - \underbrace{\frac{d\rho}{dz_S}}_{<0}\underbrace{\frac{d}{dk}(\frac{dC^m}{d\rho})}_{<0} < 0$$

Then consider the term $\mathcal{B}$:

$$\mathcal{B} = \frac{d}{dk}\Big(-\frac{dC^c}{dQ}\frac{d^2Q^*}{dz_S^2}\Big)$$
$$\underbrace{-\frac{d^2Q^*}{dz_S^2}}_{>0}\underbrace{\Big(\frac{2^{k/\rho}Q^k)(\rho + klog(2) + klog(Q^\rho))}{Q\rho}\Big)}_{>0}$$

Combining, we obtain that $\frac{d^2z_S^*}{dkd\theta} < 0$. □

Proof of Result 3

Proof. Consider a generic function $f(x, y)$. Define $\underline{\mathrm{x}}(y)$ such that $f(\underline{\mathrm{x}}, y) = 0$. Then:

- the combination of $f_y(x) > 0$ and $f_x(y) > 0$ in the vicinity of $\underline{\mathrm{x}}(y)$, form a sufficient condition for $\frac{d\underline{\mathrm{X}}}{dy} < 0$
- the combination of $f_y(x) < 0$ and $f_x(y) < 0$ in the vicinity of $\underline{\mathrm{x}}(y)$, form a sufficient condition for $\frac{d\underline{\mathrm{X}}}{dy} < 0$
- the combination of $f_y(x) < 0$ and $f_x(y) > 0$ in the vicinity of $\underline{\mathrm{x}}(y)$, form a sufficient condition for $\frac{d\underline{\mathrm{X}}}{dy} > 0$
- the combination of $f_y(x) > 0$ and $f_x(y) < 0$ in the vicinity of $\underline{\mathrm{x}}(y)$, form a sufficient condition for $\frac{d\underline{\mathrm{X}}}{dy} > 0$

Hence, to establish the result, it suffices to establish the monotonicity and sign of the derivatives of the supplier's value function $E[\Pi^{S*}](\theta, M, \beta, R_S)$ with respect to those four paramters. For this, we use the envelope theorem:

$$\begin{aligned}\frac{dE[\Pi^{S*}]}{d\theta} &= \frac{\partial E[\Pi^S](z_S^*)}{\partial\theta}\\ &= -C^m + C^c < 0\end{aligned} \tag{C.6}$$

$$\begin{aligned}\frac{dE[\Pi^{S*}]}{dR_S} &= \frac{\partial E[\Pi^S](z_S^*)}{\partial R_S}\\ &= -1 < 0\end{aligned} \tag{C.7}$$

The combination of Eq. C.6 and C.7 establishes the first part of the result.

$$\begin{aligned}\frac{dE[\Pi^{S*}]}{dM} &= \frac{\partial E[\Pi^S](z_S^*)}{\partial M}\\ &= sp^*\frac{\partial Q}{\partial M} - \frac{\partial Q}{\partial M}\frac{\partial E[C]}{\partial Q}\end{aligned} \tag{C.8}$$

Denote M^c the value of M at which this derivative is equal to 0. We show that at M^c, $E[\Pi^{S*}]$ reaches a minimum and is negative, such that $E[\Pi^{S*}]$ is monotonically increasing as M increases beyond M^c.

At M^c, $sp^* = \frac{\partial E[C]}{\partial Q}$. Plugging that into the expression for $E[\Pi^{S*}]$, we get:

$$E[\Pi^{S*}] = \frac{\partial E[C]}{\partial Q} Q^* - E[C](Q^*) - R_S z_S^* \approx -R_S z_S^* < 0 \tag{C.9}$$

Hence, Equation C.8 reaches a minimum at a value M^c above which it increases monotonically. Hence in the vicinity of $\underline{\mathrm{M}}$, the derivative is positive. Combining this fact with Equation C.6 establishes the second part of the result.

Very similarly, we have:

$$\begin{aligned} \frac{dE[\Pi^{S*}]}{d\beta} &= \frac{\partial E[\Pi^S](z_S^*)}{\partial \beta} \\ &= sp^* \frac{\partial Q}{\partial \beta} - \frac{\partial Q}{\partial \beta} \frac{\partial E[C]}{\partial Q} \end{aligned} \tag{C.10}$$

This derivative is equal to 0 at two points: when $sp^* = \frac{\partial E[C]}{\partial Q}$ (happening at β^{c_1} and when $\frac{\partial Q}{\partial \beta} = 0$ (happening at point β^{c_2}. Beyond β^{c_2}, the demand function Q saturates, having included the whole market. At this point, both the demand and profits reach a maximum, and $\frac{\partial Q}{\partial \beta} = 0$ and $\frac{dE[\Pi^{S*}]}{d\beta}$. In contrast, at β^{c_1}, the profit function reaches a minimum. By the same reasoning as in Equation C.9, the profit function is negative at that point. Suppose $E[\Pi^{S*}]$ is positive for β^{c_2} (whether this is true or not depends on parameters governing the relative importance of costs and revenues, such as c_s, M, u_0 etc...). Then by the intermediate value theorem, $\exists \underline{\beta}$ such that $\beta^{c_1} < \beta < \beta^{c_2}$, at which $E[\Pi^{S*}] = 0$ and at that point $\frac{dE[\Pi^{S*}]}{d\beta} > 0$. The combination of that statement and Equation C.6 establishes the third part of the result. □

Data Description

We use the FactSet Relationship database to obtain information about suppliers, customers and competitors. FactSet contains the most comprehensive relationship database currently available. It covers relationships for a large number of public and private firms between 2003 and 2017. The database includes information publicly reported by firms[19], and complements this information using firms' SEC filings, press releases, public announcements, investor presentations, and firms' websites. Importantly, the database analysts update relationships on an annual basis. The unit of observation in the FactSet Relationship database is a relationship between two firms. The relationship can be labeled as 'supplier', 'customer', or 'competitor'[20]. The database also indicates the beginning and end dates for each relationship. Firms are identified by a FactSet id, and firms' name are also available.

We choose to focus on the car manufacturing sector. To this end, we first collected names of firms listed under the NAICS code 33611, that is "automobile and light duty

[19]In particular, Regulation SFAS No. 131 requires firms to report customers representing more than 10 percent of the firm's sales.

[20]Other types of relationship, such as partnerships, are also indicated.

motor vehicle manufacturing". We obtain a list of 48 companies (examples include Ford, Toyota, Tesla...). We then use FactSet Revere to obtain information about those firms' relationships. Unfortunately firm FactSet ids do match standardized ids, such as ISINs, we identify firms by matching on names. Furthermore, we only keep in our sample firms that are labeled as being competing against each other. Hence, we obtain a list of 27 companies, and use the FactSet Relationship database to obtain data on supplier relationships between 2003 and 2017. We construct a panel dataset where the observations are at the producer-year level. For example, we observe the number of suppliers each producer work with in a given year, as well as the duration of such relationships.