Green Technology Adoption: An Empirical Study of the Southern California Garment Cleaning Industry *

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Abstract

New technologies are crucial in dealing with the problem of air and water pollution, which is an increasingly important issue with serious health and environmental consequences. Adoption of environmentally friendly technologies can be slow if the new technologies are not superior in terms of the firms' private incentives, if firms have long equipment replacement cycles, or if firms do not have sufficient information to evaluate whether or not a switch to a green technology is in their private interests. To evaluate these potential explanations and the policies designed to address them, this paper uses importance sampling to estimate a dynamic durable good replacement model for garment cleaning firms in southern California. The standard dry cleaning technology uses perchloroethylene (perc), a toxic air and ground contaminant, and the alternative technologies have seen only limited adoption to date. The model controls for and exploits changing legislation to estimate the effect of fees and incentives on green equipment purchases, as well as the effect of product demonstrations. The estimated model is used to compare the predicted adoption and entry/exit decisions by firms under different regulatory regimes. While the model is tailored to the garment cleaning industry, it can be adapted to other applications involving the diffusion of socially better technologies.

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1 Introduction

The adoption of new, cleaner technologies is essential in reducing pollution. Even if the technologies have already been developed, the empirical technology diffusion literature has demonstrated that the diffusion of new technologies can be slow (Bass 1969, Mahajan, Muller & Bass 1990, Hannan & McDowell 1984, Mulligan 2003, Baker 2001, Engers, Hartmann & Stern 2009). There are a variety of potential explanations for slow adoption: i) firms do not realize the full societal benefits of using the green technology and the green technology is not superior in terms of the firms' private incentives; ii) firms may have long equipment replacement cycles which have slowed the migration to a socially and privately better technology; or iii) firms may not have sufficient information to evaluate whether or not a switch to a green technology is in their private interests.[1] Government intervention is often used to expedite the adoption of the cleaner technologies, in order to reduce the difference in the private and social values of adoption. Firm decisions are therefore affected by a mix of firm variables including product quality, pricing and advertising in concert with government pricing, advertising, and possibly regulation.

When there are important dynamics to consider, as in the case of durable goods, it is becoming more common in the marketing and economics literature to structurally model an agent's decision to adopt a new technology (Gowrisankaran & Stavins 2004, Tucker 2008, Gordon 2009). A structural analysis of firms' adoption decisions allows for the estimation of policy-invariant profit function parameters which can be used to assess the different tools used by policymakers, or firms, to expedite the adoption of the different technologies. The application studied here is garment cleaning, which i) involves the purchase of durable goods and faces just such a mix of policies to drive adoption; ii) has readily available public data; and iii) has experienced variation in policies over time that have altered both current variables and the expectations of the future, which drive the identification of dynamic models.

I construct and estimate a single agent, dynamic durable good adoption model adapted from Rust (1987) that explicitly solves for firms' solutions to their dynamic optimization problems, as is

[1] The theory literature on technology adoption has demonstrated that uncertainty in new technologies may create barriers to adoption, which are even larger in the case of durable goods (Jensen 1982, Farzin, Huisman & Kort 1998, Doraszelski 2001).

common in the literature (Nair 2007, Hartmann & Nair 2009, Smith 2010).[2] I estimate the structural primitives of the model using importance sampling (Ackerberg 2009) as done in Hartmann (2006), Bajari, Hong & Ryan (2009), and Goettler & Clay (2010) in order to include rich heterogeneity which I would expect due to the environmental nature of the application. Potential reasons for heterogeneity in profits when using different types of equipment include differences in marginal costs or in the prices firms are able to charge consumers for cleaning since the demand for cleaning equipment reflects the demand for garment cleaning. This is the only application of importance sampling of which I am aware that includes entry and exit in a dynamic setting with heterogeneity and controls for the endogeneity of the initial market conditions regarding which agents are in the market at the start of the panel.

In this paper, I use the exogenously changing environmental policies in southern California to help identify the distribution of heterogeneity in firms' profit parameters, which I then use to evaluate the California policies with several alternatives. Although I use California data, I am able to assess how outcomes would have changed if other policies, such as those in a neighboring state, Oregon, were used instead. The dynamic, structural model allows firms and/or governments to predict green technology adoption under varying combinations of pricing for equipment and inputs, product demonstrations, and potentially, outright bans. The two examples, California and Oregon, allow me to compare one set of policies that uses a mixture of policy tools including a ban on the polluting technologies with another that only uses a market-based incentive (a tax on the polluting solvent). To preview my results, both sets of policies lead to increased adoption of the green technologies, and while there is a large effect of demonstration sites on the adoption of the demonstrated technology, most of this extra adoption is by firms who would have adopted one of the other green technologies. There is less exit under California's policies which is mostly offset by reduced entry.

The rest of the paper is organized as follows: In the next section, I provide background regarding the garment cleaning industry and the policies designed to phase out perc, and in section 3 I describe the data. My model and estimation strategy are outlined in section 4 and the results are

[2]Two-stage methods such as Hotz & Miller (1993) and Bajari, Benkard & Levin (2007) are unsuited to this application since there are a limited number of adoptions of the green technologies, significant heterogeneity, and lots of variation in the policies.

presented in section 5. Section 6 provides a discussion of the results and I use the structural parameter estimates to perform counterfactual market simulations which are presented in 7. Section 8 concludes.

2 Background

2.1 Industry Background

Laundry services and garment cleaning is a $22.6 billion dollar per year industry, according to the 2007 U.S. Census Bureau's Annual Services Survey (Hambric 2008). The standard technology used in garment cleaning requires the use of perchloroethylene (perc), a toxic, cancer-causing air and ground contaminant used by approximately 28,000 U.S. dry cleaners nationwide according to the Environmental Protection Agency (EPA). The issue is of such importance that the State Coalition for Remediation of Drycleaners was established in 1998, with support from the EPA, in order to aid in the development of remediation programs to clean up contamination caused by the use of perc.[3] A document was released by the EPA in 1992 summarizing the hazards associated with exposure to perc, and since then the use of the chemical has come under more and more scrutiny. Currently, the EPA is considering whether to compel dry cleaners to phase out perc nationwide, according to a recent article in the Washington Post.[4] The California Dry Cleaning Industry Technical Assessment Report was published in 2006 as part of the 1993 Airborne Toxic Control Measure for Emissions of Perchloroethylene from Dry Cleaning Operations and provides a detailed description of the California garment cleaning industry(Fong, Chowdhury, Houghton, Komlenic & Villalobos 2006). The California Air Resources Board (CAARB) 2003 facility surveys estimated that there were around 5040 cleaners, 4670 of which used perc.

Most types of equipment that use perc (and most of the alternative solvents) are closed-loop machines meaning that the washing, extraction and drying of the garments all occur within the

[3] Thirteen states are members of the coalition.

[4] Washington Post, Wednesday, April 8, 2009, page A03. http://www.washingtonpost.com/wp-dyn/content/article/2009/04/07/AR2009040703748.html

same machine. To dry the clothes, air is pulled in from outside and then released. Different control methods have been developed to reduce the emission of perc into the air during the drying process, primarily refrigerated condensers which cool the air before emitting it back into the atmosphere. Perc emissions also occur at the end of the cleaning cycle when the drum is opened to remove the clothes. Secondary control methods help to trap perc before the clothes are removed. However, despite the control technologies, a significant amount of perc still escapes during the cleaning process.

Although the majority of cleaners use perc equipment, alternative cleaning technologies are available. Some equipment use hydrocarbon or fluorocarbon solvents (also known as mineral spirits) instead of perc. The process is quite similar to perc cleaning. There are a few other solvents used as perc replacements but most of them also have health or environmental risks associated with them. Decamethylcyclopentasiloxane, the chemical found in the silicon-based GreenEarth solvent has been found to have similar efficacy to perc and has low solubility in water, thus reducing water pollution.[5]

Carbon dioxide (CO2) and wet cleaning are considered to be the cleanest perc alternatives. CO2 cleaning is a closed-loop process that uses pressurized carbon dioxide, a non-toxic, naturally-occurring gas. The liquid CO2 and detergent are circulated through the clothes with the use of jets inside the cleaning equipment. The dirt is removed with the CO2 during the drying process. It is a gentle cleaning process with a longer drying cycle than perc cleaning. There are three U.S. manufacturers of CO2 equipment.

Wet cleaning was developed in 1991 and requires special equipment and a higher level of control throughout the cleaning process that the other types of cleaning. The washer and dryer are separate pieces of equipment, and like CO2 cleaning, the drying process is longer than for perc cleaning. Unlike when using the previously discussed technologies, tensioning equipment is needed to restore the clothes after wet cleaning to their original shape. More training is required for employees when using wet cleaning equipment in order to understand the process and ensure efficacy.

[5]Research is ongoing as to whether it is a carcinogen.

The road to perc regulation began in 1991 when the CAARB determined that perc is a toxic air contaminant which falls under California's Toxic Air Contaminant Identification and Control Program. In 1993, the CAARB adopted the Airborne Toxic Control Measure for Emissions of Perc from Dry Cleaning Operations (Dry Cleaning ATCM) and the Environmental Training Program for perc dry cleaning operations. These measures set new requirements for cleaners in an effort to reduce air contamination.

The South Coast Air Quality Management District (SCAQMD) is the air pollution control agency for all of Orange County and the urban portions of Los Angeles, Riverside and San Bernardino counties. It has the largest number of cleaners in the state and has been very aggressive in its plan to phase out perc, even more so than the CAARB. The SCAQMD is looking to eliminate the use of perc machines by the end of 2020, recognizing the durable nature of the equipment in its phase-out plan. SCAQMD Rule 1421 was first passed on December 9, 1994, but the final version was updated December 6, 2002. It states that "On or after January 1, 2003, an owner or operator of a new facility may not operate a perchloroethylene dry cleaning system. On or after December 6, 2002, an owner or operator of an existing facility shall be allowed to operate its perchloroethylene dry cleaning system(s) until the end of its useful life[6] and, upon replacement, shall be allowed to operate no more than one perchloroethylene dry cleaning system per facility until December 31, 2020."

In December 2002, the SCAQMD also instituted a grant program for dry cleaners willing to upgrade to cleaner technologies, including carbon dioxide, wet cleaning, hydrocarbon and GreenEarth. There is no consensus as to which technologies should be labeled as green. In this paper, I refer to all non-perc cleaning technologies as green technologies although carbon dioxide and wet cleaning are the most environmentally-friendly. The SCAQMD grants give $10,000 to dry cleaners willing to switch to carbon dioxide cleaning,[7] $10,000 to switch to wet cleaning, and $5,000 to switch to hydrocarbon or GreenEarth.[8]

[6]The "useful life" of the equipment is something that came under rigorous debate between the SCAQMD and the California Cleaners Association(CCA), the SCAQMD wishing to set the useful life at ten years, the CCA at 20. A 15 year useful life was the compromise.

[7]The CO2 incentive was recently changed to $20,000.

[8]The grants for GreenEarth were soon discontinued, in 2003, and hydrocarbon grants were discontinued in 2007.

In addition, the state of California passed Assembly Bill 998 (AB 998) in August 2004 which established the CAARB's own non-toxic dry cleaning incentive program. The CAARB incentive program gives $10,000 grants to dry cleaners using perc if they are willing to switch to either carbon-dioxide or wet cleaning technologies. The Air Resources Board plans to completely phase out perc dry cleaning machines state-wide by the year 2023. The CAARB grants were not available for the purchase of hydrocarbon or GreenEarth equipment. The majority of the funding for the CAARB dry cleaning program comes from fees imposed on the purchase of perc solvent (under AB 998). The fees began in 2004 at three dollars per gallon of solvent and increase by one dollar annually until 2013, when they are $12 per gallon.

AB 998 also requires the CAARB to use its funds to support a demonstration program which provides dry cleaners with the opportunity to learn about green cleaning technology, primarily wet cleaning, at various locations across California. Technical assistance and training are provided through the program in an attempt to reduce the costs and supply information regarding the benefits and overall effectiveness of carbon dioxide and wet cleaning technologies, although I only observe wet cleaning demonstration sites in southern California. The sites are usually garment cleaning firms who receive a subsidy to become a demonstration site. On one day, other cleaners are invited to come walk through the wet cleaning process to see for themselves how to use the new cleaning method and how effective the cleaning is. These sites have the ability to reduce uncertainty in the new technologies or may lead firms to update their prior beliefs regarding the effectiveness of the new technology. The time-dependent geographic proximity of demonstration sites (as they are established) to potential adopters can be used to estimate the barriers to adoption which are eliminated by the provision of this information and training. According to the CAARB website, "Demonstration sites ultimately will, in time, create the regional and statewide infrastructure necessary for the long-term diffusion of these technologies." Lastly, on January 25, 2007, California legislators amended the Dry Cleaning ATCM. The amended ATCM prohibits the sale or lease of new perc dry cleaning machines beginning on January 1, 2008.[9] This was a drastic policy shift away from the gradual phase-out plan and is reflected in the data.

[9] In addition, it forbids the use of existing perc machines at co-residential facilities and requires the removal of perc machines that are 15 years or older by July 1, 2010. All other perc machines must be removed from service once they become 15 years old or by January 1, 2023, whichever is sooner. The law also requires expanded record keeping by perc facilities and manufacturers.

According to the president of the California Cleaners Association (CCA), the cleaners have been working with the California Air Quality Management Districts across the state to try to limit the financial costs of the phase-out. However, the many changes in the regulations were unanticipated by the cleaners who had limited ability to alter the legislation. Even the compromise of 15 years as the regulated useful life of perc cleaning equipment is now potentially going to be altered by the San Francisco Bay Area AQMD which is considering legislation to change the legal useful life of perc equipment to 10 years. The cleaners are being forced into the transition away from perc, and the CCA is now concerned that new legislation might force cleaners away from the use of hydrocarbon cleaning as well, which is considered by many cleaners to be the most cost-effective technology after perc, according to anecdotal evidence. According to the CCA, cleaners are already being forced out of business by the new regulations and more restrictions will make the problem considerably worse.

3 Data

3.1 Data Sources

Permits This paper uses permiting data available through the SCAQMD. I have the dates at which all permits were granted to perc and hydrocarbon dry cleaners in the SCAQMD which encompasses most of southern California. These permit data also track changes of firm ownership since new owners need to re-permit their equipment. A total of 14,877 permit applications by 4,270 cleaners were filed with the SCAQMD between 1956 and 2008, resulting in 13,172 permits. In this analysis I treat cleaners after an ownership change as the same firm. Most of the cleaners that appear in the SCAQMD data have perc equipment but some fraction of the cleaners have equipment that uses hydrocarbon or other petroleum solvent.

The data include each facility's name, address and phone number, as well as the type of equipment, whether a permit was issued (usually the case) and the date the permit was issued. Since 1996, the SCAQMD has also kept track of whether facilities have gone out of business or become inactive for some other reason. I also have access to permit diary files which track firm actions in 1982 and later. I can use these data to determine whether firms exited the market prior to 1996, assuming that firms that inactivated a permit with no new permit left the market. Unfortunately, these diary files are not complete. If a firm is included in the data and has not purchased equipment since before 1983, I assume it is inactive and use the last SCAQMD inspection date as the exit date. It is important to include the firms that exited to make sure I do not underestimate the probability of exit under the new policies.[10]

Green Cleaners The data on cleaners using wet, carbon dioxide or GreenEarth cleaning come from a variety of sources. The first source is the list of SCAQMD grant recipients. The grants began in 2003 and included incentives for adopting hydrocarbon, wet cleaning, carbon dioxide, and GreenEarth cleaning technologies. The GreenEarth grants were discontinued after one year and the hydrocarbon grants were eliminated after 2007. Only the incentives for wet cleaning and carbon dioxide are still in place, and in 2007, the carbon dioxide grants were retroactively increased to $20,000. There were 596 SCAQMD grant recipients by the end of 2008.

The second data source is the list of CAARB grant recipients. In 2005, the CAARB began their garment cleaning grant program, but only for cleaners switching to wet cleaning and carbon dioxide. In addition, cleaners taking the CAARB grants are required to remove their perc equipment from the facility and commit to not purchasing perc equipment in the future. There have been 85 recipients between 2005 and 2008 from all of California.

In addition, a list of green cleaners was acquired from the Urban & Environmental Policy Institute (UEPI), a community oriented research and advocacy organization based at Occidental College in Los Angeles, CA. The UEPI website allows consumers to search for green cleaners (which they define to be wet or carbon dioxide cleaners) that are within a given radius of a user-provided address. Their database includes 166 wet and carbon dioxide cleaners in California. The ability for consumers to search for cleaners using the cleaner technologies is one potential benefit

[10] I first remove superfluous actions when a firm inactivates and actives a piece of equipment in the same or adjacent years, presuming it is the same piece of equipment. I also remove firms which I assume are inactive but cannot establish an exit date, which is the case for 23 firms. I also remove a few firms which do not do anything for a span of at least thirty years, and I therefore assume I have missing exit actions. There are 6 of these firms.

to adoption.

Finally, I use the SCAQMD permit diary files to identify if a permit was inactivated in order to switch to a different technology. This identification of green cleaners depends on the diary description variable and provides me with information for cleaners who purchased green equipment before the incentives were available.

Demonstration Sites Under the CAARB demonstration program, there were 26 demonstrations of either wet cleaning or carbon dioxide cleaning before 2009 at 18 different sites in California. Of these demonstration sites, 17 of them were cleaners who chose to become demonstration sites and received a CAARB incentive to purchase wet or carbon dioxide cleaning equipment and an additional incentive to become a demonstration site. The UEPI also sponsors a green cleaning demonstration program, in cooperation with the CAARB. There have been 30 total demonstration sites in California, thirteen of which are located in the SCAQMD region and which occurred during my period of study (1999-2008). These thirteen demonstration sites were all wet cleaning locations.

Other Data I include firm data from Reference USA to explain some of the heterogeneity in profit parameters across firms. These data include variables from 2008 including sales, number of employees, credit rating, and square footage of the facility. Except for credit rating, the variables are in bins of discrete size with only a few realized values for each variable, which limits their value. I also only have data for currently active firms. I merged the cleaners from the above data with the Reference USA data, which include garment cleaning drop-off locations in addition to cleaners who do their own cleaning. There were 2,225 matches; the Reference USA data only include information for cleaners which are currently active. There are 2,701 cleaners who do not appear in the permitting data; most likely, they are cleaners who outsource their cleaning.

In addition to the firm-specific variables available through Reference USA, I include zip-code level variables which may explain heterogeneity in demand for garment cleaning or green cleaning specifically. These variables include income, family size, ethnicity and age, as well as variables that may indicate a preference for green alternatives, such as the fraction of commuters who carpool, walk or use public transportation and the relative number of hybrid vehicle purchases. These data were assembled from American Factfinder, Sourcebook America and a proprietary dataset on vehicle registrations from R.L. Polk and Company.

3.2 Data Summary

I combine the different data files by doing an address match between firms in the SCAQMD data and in the other data sets. Of the different technologies, my data include cleaners which have adopted hydrocarbon, wet, carbon dioxide, and GreenEarth cleaning equipment. The estimated costs for these different types of equipment can be found in Table 1, along with average annual operating costs exclusive of labor.[11]

I geocode the firm and demonstration site locations to calculate the distances between the firms and all of the demonstration sites in every given year. I limit the analysis to the years 1999-2008 for a variety of reasons. First, I do not have complete facility action data before 1996. Second, this is after firms are aware of the issues surrounding perc cleaning since the period follows the CAARB's formal classification of perc as a toxic air contaminant in 1991, the 1993 passing of the CAARB ATCM, and the SCAQMD's passing of the original version of Rule 1421 in 1994. Finally, it is desirable because CAARB Rule 1421 forbids the use of transfer or vented perc machines after 1998, and as a result, I see a relatively large number of firms (388) exit the market in that year. Since I cannot identify which perc machines are of these types, I cannot control for this strict command-and-control regulation since there is no way to determine if firms that bought new equipment or exited the market did so because of the mandate. In the analysis, I do still assume a stationary equilibrium in 1999, which is reasonable considering that firms can convert their vented machines to closed loop machines.

[11]More detail can be found in the CAARB California Dry Cleaning Industry Technical Assessment Report. Operational costs follow the same trends as the machinery costs: Carbon dioxide cleaning has high capital and operational costs but wet cleaning actually has lower costs than traditional perc cleaning. However, this does not account for the extra training required to use the greener technologies or the fact that wet cleaning is more labor intensive than traditional dry cleaning.

I use the permit data to compute the age of each cleaner's equipment over time. I keep track of the age of their most current equipment only. There are 3,534 cleaners in the combined data set, but not all of these cleaners are active at the same time. In any year, there are just over 3,000 active cleaners. To get a sense of the current industry size and level of green technology adoption, Table 2 breaks down the technology used by those cleaners which were active at the end of 2008. In addition, it includes the average distance to the nearest demonstration site.[12] While there has been considerable adoption of hydrocarbon cleaning, and some adoption of wet cleaning, there has been little adoption of GreenEarth and only four firms have adopted carbon dioxide. Not surprisingly, the average distance to the nearest demonstration site is smaller for cleaners who are now using wet (or carbon dioxide) cleaning.

Due to the limited number of observations for cleaners choosing the cleaner technologies, it is useful to tabulate the cleaners' actions by current equipment type and age, as well as by year. Table 3 shows how the actions of cleaners depend on the current type of equipment owned. This table will determine what I can actually identify in estimation. Since I do not observe cleaners who have purchased wet, carbon dioxide or GreenEarth equipment exit the market or purchase other equipment in subsequent years, I will be restricted in my ability to separately identify the utility of purchasing equipment from the utility of utilizing the equipment.

Table 4 separates the actions by the age of the previous equipment. There are more purchase actions than I would expect when the age of the existing equipment is low. Some of this is likely a result of assuming new permits are for new equipment, when in fact the permitted equipment may be used. I try to limit these errors by ignoring new permits if I observe the previous equipment being deactivated in the permit diary files. Also, according to garment cleaning facility survey results in the 2006 CAARB technical assessment report, 89% of machines are bought new and 96% of owners said they would buy a new machine in the future, these errors should be kept to a minimum and not have a discernable impact on the results.

Another explanation for the large number of new equipment purchases when the previous equipment is only a few years old is the changing regulations. In particular, the CAARB restriction

[12] Other than themselves if they became a demonstration site.

against perc purchases after 2007 likely led cleaners to purchase new equipment when they may have otherwise waited. Many of the perc equipment purchases when the previous equipment was relatively new took place in 2007. A final explanation could be that age simply does not matter much, either because there is limited machine depreciation or because there is relatively efficient secondary market for used equipment, in which case depreciation would be reflected in the scrap value upon exiting as well as when cleaners use their old equipment.

Table 5 shows which actions occurred in which years. There are a few features of the data that are notable. One is that in 2003, the year in which both the 2004 Assembly Bill was announced and the SCAQMD incentives began, I observe many more green equipment purchases. There appears to be a large effect of the SCAQMD and CAARB incentives in the years they are offered; in particular, most GreenEarth purchases occur in 2003, the only year the incentives were available; there is also a drop in the average age of firms who buy wet cleaning equipment and exit the market in this year, and the age for firms who buy GreenEarth equipment is also at its lowest point.

One of the most striking observations in the data is what occurred in 2007 when it was announced that cleaners would not be able to purchase perc equipment in later years. There is a large spike in perc purchases in 2007. One would expect some increase since it was announced at the beginning of the year that it is the last year to purchase perc equipment, but the magnitude of the increases seem to indicate that there are some firms who are very reluctant to switch technologies. The average age of firms buying perc equipment drops by two years, which provides evidence that firms are purchasing perc before they would have done so due to this new regulation forbidding perc purchases after that year. Hydrocarbon purchases also experience a modest spike in this year, possibly since this was the last year the hydrocarbon grants were available.

4 Model and Estimation

4.1 Firm Profits

I expect firm profits to depend on the type of technology used. Differences in profits across the technology types could be from a variety of sources including equipment purchase costs, fixed costs, operating costs such as solvent and electricity use, and markup which will depend on consumers' willingness to pay for cleaning performed by that type of equipment. A firm's ability to charge a different markup depending on the type of technology would imply quality or perceived quality differences between the technologies. The firms which have adopted carbon dioxide cleaning are all located in affluent areas where consumers may be willing to pay a premium for environmentally friendly cleaning. On the other hand, wet cleaning, although environmentally friendly, may have negative connotations if consumers are concerned about the efficacy of the cleaning or potential damage to the clothes by this more radical technology.

Because of the large capital costs and the durable nature of cleaning equipment, as well as the changing regulatory environment, cleaners are modeled as forward-looking profit maximizers. The model developed in this paper is a single-agent, regenerative optimal stopping model adapted from Rust (1987), allowing for entry and exit. In each period, a dry cleaner faces the decision whether or not to remain in the market, whether to invest in new machinery, and if so, what type to invest in. Let the choice-specific profit function for cleaner i be given as:

$$\pi(x_{i\tau}, j_{i\tau}, \psi_t, s_{it}|\beta_i) + \varepsilon_{ij\tau}, \tag{1}$$

where $j_{i\tau}$ is the choice at time τ. The choice set $C_t(\tau)$ includes the following choices: $j = 0$ (exit), 1 (no investment), 2 (purchase perc equipment), 3 (purchase hydrocarbon equipment), 4 (purchase wet cleaning equipment), 5 (purchase carbon dioxide equipment), 6 (purchase GreenEarth equipment). After 2007, the choice to purchase perc equipment is removed from the choice set. I assume that the unobserved profit shock, $\varepsilon_{ij\tau}$, enters the profit function linearly and follows an iid type 1 extreme value distribution.[13]

[13]Since I impose the condition of conditional independence of the unobservable state variable I assume that all de-

I define $x = \{e, w, t\}$ as the vector of observable state variables including e, the current technology used by the firm (or if the firm is a potential entrant), equipment age w which I define as the number of years since purchase within which the equipment is operating ($w = 1$ if the equipment is new), and the year t. A firm's technology and the age of its equipment evolve according to the following laws of motion, where P_t is a dummy variable indicating an equipment purchase:

$$\begin{aligned} w_t &= w_{t-1} + 1 \text{ if } P_t = 0 \\ e_t &= e_{t-1} \text{ if } P_t = 0 \\ w_t &= 1 \text{ if } P_t = 1. \\ e_t &= j_t \text{ if } P_t = 1. \end{aligned} \tag{2}$$

This simply says that the equipment age increases by one and the type of equipment stays the same if no new equipment is purchased, and the age is immediately reset to one and the equipment type changes to the purchased equipment if new equipment is purchased. This assumes that cleaners can use newly purchased equipment immediately. The age variable is set to one for potential entrants, and in each period I assume there is a new set of potential entrants.

Time enters the firms' value functions due to the changing environmental legislation, $\psi_t(e, \tau) = \{f_t(e, \tau), g_t(e, \tau), C_t(\tau)\}$, which includes the equipment-specific fees, equipment-specific grants, and the consideration set, respectively, all of which depend on the year τ. However, since the policies change over time, the policies are actually expected policies based on the information available to cleaners in year t, and they affect profits in all current and later τ. In other words, (1) is the expression for *expected* profits in any year $\tau \geq t$, where the expectation is taken in the current year t. Firms maximize their total profits over the current and future years given their expectations of future grants, fees, and technology restrictions. In addition, s_t is an *unobserved* state variable which is equal to one for wet cleaning only, if the owner of the cleaner has attended a wet cleaning demonstration by current year t.

To allow firms to be forward-looking profit maximizers, I need to make some assumptions

pendence of the unobservables are accounted for through the observable state vector. Although I do acknowledge that there may be serial correlation in the error terms, I hope that any correlation will be accounted for with the inclusion of firm heterogeneity.

regarding cleaners' expectations. I assume that firms do not anticipate the entry of demonstration sites or the policy changes before the public hearings are held to announce the proposed changes. Indeed, one of the biggest complaints by cleaners is that the regulations are always changing and cannot be anticipated. I use the years of these hearings as the years in which firms learn about the future policies, and I assume that firms maximize their expected future profits under the new policy regime (with no uncertainty). After talking with individuals in the industry, I feel that these are reasonable assumptions. However, although it seems reasonable to assume that the restrictions and fees in the new policies are considered by firms to be permanent changes, the same is not necessarily true for green technology purchase grants. The SCAQMD does not specify its funding source and makes clear the fact that grants will be awarded on a first-come, first-served basis. The CAARB receives its funds from the perc fees, some of which are required by AB 998 to support the demonstration program. It is not clear whether firms expect these grants to be available in later years, although I was told by an administrator at the CAARB that cleaners may not take future grants as a given. I estimate the model under both assumptions and utilize a likelihood ratio test to evaluate them.

I assume the deterministic component of expected profits in year $\tau \geq t$ under the year t policies are equipment specific and given by the following expression:

$$\pi(x_{i\tau}, j_{i\tau}, \psi_t, s_t|\beta_i) = \beta_e + \beta_v s_{it} + \beta_w \log w_{i\tau} - \beta_f f_t(e_{i\tau}, \tau) + (-\beta_K(K_e - g_t(e_{i\tau}, \tau)) + \beta_P) P_{i\tau} + \beta_B B_{i\tau}.$$

Again, $f_t(e_{i\tau}, \tau)$ are the announced solvent fees for equipment $e_{i\tau}$ at time τ (perc is the only taxed solvent in California) and $g_t(e_{i\tau}, \tau)$ are the equipment grants, which reduce the capital costs K_e when the cleaners purchase new equipment, as indicated by the purchase dummy variable, $P_{i\tau}$. The units are in \$10,000, and the perc fees are the fees per 46,600 pounds of clothes cleaned, the average annual amount by one cleaner. Since the fees and equipment costs will lead to lower profits, I include negative signs for these terms and constrain the parameters to be positive. $B_{i\tau}$ is a dummy variable indicating if the cleaner in a new entrant in which case it faces an additional entry cost.[14] The scrap value received upon exiting the market is normalized to zero.[15]

[14] I assume that potential entrants have the information and training that is acquired by visiting a demonstration site i.e. $v_{i\tau} = 1$ since it is likely they are well informed regarding the use of the new technologies.

[15] After 2003, firms with perc equipment older than 15 years old have to discontinue use of the equipment. I do not

The profit function when firms use their existing equipment depends on the equipment age, reflecting the fact that there are maintenance costs and/or expected losses from machine failure associated with using older equipment but not with new equipment (in which case the age term is equal to zero, by construction). I assume age enters through a concave function to allow for rapid initial declines in value (which is consistent with secondary market values for durable goods). As a robustness check, I allowed age to enter in a more flexible manner, but I found the same, concave effect so I report the results using the log specification.[16]

The profit intercepts depend on the type of equipment being used, $s_{i\tau}$. However, since the costs of each type of equipment are not the same, I include the average fixed cost of each type of equipment, K_e[17] when firms purchase new equipment; I also allow for unobserved purchase costs, β_{iP} which I assume are not equipment-specific. I use known average equipment costs because I cannot separately identify the utility of utilizing equipment from that of purchasing equipment. Since I am studying the industry as it just begins to evolve towards the use of alternative technologies, I observe very limited behavior by cleaners with green equipment. Although I observe wet, carbon dioxide and GreenEarth cleaners in the market, they make no subsequent purchases in the years after their green purchases and they do not exit, and so I cannot separately identify the utility of owning versus purchasing these green types of equipment; at most I can put an upper bound on the purchase utility of the green equipment. However, because I observe cleaners using perc exit, operate existing equipment, and purchase new perc equipment, I can separately identify the purchase and utilization utility for perc equipment, so if I assume that the unobserved purchase costs β_{iP} are not equipment-specific, then I am able to separately identify this parameter through the behavior of perc firms.

Equation 3 allows wet cleaning profits to be different if the owner of a cleaning facility has attended a wet cleaning demonstration. However, I do not observe whether or not this is the case,

always observe these firms immediately exit the market or buy new equipment, so I allow for this small minority of firms to remain in the market with profits equal to an estimated intercept. These firms may be outsourcing the cleaning or actually be inactive, waiting to purchase new equipment in a later year, and I do not attempt to distinguish between the two.

[16]I also tried allowing equipment age to enter into the profit function when purchasing new equipment since there may be age-dependent scrap value which differs from that when exiting the market, but I found this coefficient to be imprecisely estimated and close to zero.

[17]As reported in the 2006 CAARB report.

i.e. $s_{i\tau}$ is unobserved. I solve for firms' value functions under both conditions and use a separate model of demonstration site visitation to incorporate the probability a cleaner has attended a demonstration in the estimation procedure.

4.2 Value Function Computation

I solve for the value function explicitly. Cleaners' expected total profits are calculated by summing up the current and discounted future profits:

$$V(x_{it}, \psi_t, s_{it}|\beta_i) = E\left[\sum_{\tau=t}^{\infty} \rho^{\tau-t} \sup_{j_{i\tau} \in C_t(\tau)} \left[\pi(x_{i\tau}, j_{i\tau}, \psi_t, v_{it}|\beta_i) + \varepsilon_{ij\tau}\right]\right]. \tag{3}$$

The time subscript on ψ and v on the right hand side is t since the policies in future years are expected to be the same as the current announced policies, and the cleaners are assumed to not anticipate more demonstrations in future years. In the years before the state regulations began in late 2002 and after the 2020 phase-out, there is a stationary equilibrium i.e. the value function is time-independent and is the fixed point solution to the following Bellman equation (dropping subscripts for notational convenience):

$$\overline{V}(x, j, \psi, s|\beta) = \pi(x, j, \psi, s|\beta) + \rho E_{x', \varepsilon'|x,j}\left[\max_{j' \in \mathbb{C}_t(t)} \left[\overline{V}(x', j', \psi, s|\beta)\right]\right], \tag{4}$$

where ρ is the discount factor. Expected total profits before realization of ε are:

$$V(x, \psi, s|\beta) = E_{\varepsilon}\left[\max_{j \in \mathbb{C}_t(t)} \overline{V}(x, j, \psi, s|\beta) + \varepsilon_j\right].$$

Given a particular policy regime, I solve for the fixed point to the above Bellman equation for what the industry will look like in 2020, when the SCAQMD has said that perc machines may no longer be used, and for the pre-2003 period before any of the new incentives or fees were announced. Then I calculate the non-stationary value functions for the years between 2003 and 2020 using equation (4), working backwards from my fixed point solution for the value function in 2020. I have to recompute these value functions every time there is a policy change. Before any policies are announced, cleaners' stationary value functions for all years are those calculated for the pre-regulation period since the cleaners do not anticipate the future regulations. The value functions are different in 2003 when the policies are first announced. In the aforementioned example, before it was announced in January 2007 that no sales of perc machines for use in California would be allowed after 2007, firms expected that they would be able to continue to buy perc machinery until 2020 and the value functions were computed under these expectations. Firms' value functions in 2006 were quite different than in 2007 when firms' expectations changed as a result of the announcement.

4.3 The Effect of Demonstration Sites

I solve the value function for firms whose owners have and have not visited a demonstration site, setting s_{it} to be equal to one and zero, respectively. The probability that a firm i takes action j at time t can be expressed as:

$$P(j_{it}|x_{it}, \psi_t, s_{it}, \beta_i) = \frac{e^{\overline{V}(x_{it}, j_{it}, \psi_t, s_{it}|\beta_i)}}{\sum_{k \in \mathbb{C}_t} e^{\overline{V}(x_{it}, k_{it}, \psi_t, s_{it}|\beta_i)}}, \tag{5}$$

where $s_{it} = 1$ for wet cleaning if the owner visited a demonstration site and zero otherwise.

The probability that the owner of a cleaning facility visits a demonstration site will depend on the value of visiting relative to the costs imposed. The value for visiting a site will depend on the current state: firms who are more likely to replace equipment in the current period will have a higher value from visiting. The value of attending demonstration site k if the cleaner has not yet attended a demonstration is:

$$V^s(x_{it}, \psi_t|\beta_i) = V(x_{it}, \psi_t, s_{it} = 1|\beta_i) - V(x_{it}, \psi_t, s_{it} = 0|\beta_i) + \beta_d d_{ik} + \eta_{it}, \tag{6}$$

where d_{ik} is the distance to the demonstration site and η_{it} is assumed to be a logit error. Without observations of actual visits, I cannot identify the scale of the error term. I normalize the variance to be that of ε_{it}, the error term when choosing between equipment types. The results are fairly robust to alternative assumptions on the variance of η_{it}, although if I assume deterministic probabilities (i.e. no error term) then I eliminate the possibility of contributions from multiple demonstration sites in the probability of visiting, since the probability of visiting each site will be zero or one, and the benefit from visiting only depends on having visited at least one site. The probability of attending demonstration k (occurring in year t) if the cleaner has not already attended one is given by:

$$P_{ik}^s = \frac{e^{V_k^s(x_{it},\psi_t|\beta_i)}}{1+e^{V_k^s(x_{it},\psi_t|\beta_i)}}.$$

The probability a cleaner has visited *at least one* demonstration site by time t is given by:

$$P_{it}^s = P_{iK}^s, \tag{7}$$

where K is the most recent demonstration and I define P_K^s, the probability that the owner of a cleaner has visited at least one demonstration site at time t, recursively:

$$\begin{aligned} P_K^s &= P_{K-1}^s + (1-P_{K-1}^s)P_{kt}^s, \\ P_0^s &= 0. \end{aligned} \tag{8}$$

This formulation of how demonstration sites affect profits has a couple of desirable features. First, by letting a demonstration site affect firm profits in the current and later periods, I allow for owners to attend a demonstration in one year to acquire information and training in the use of wet cleaning, and their profits will be affected if they then switch to wet cleaning in a later year. Although this could have been done by including the distance to the nearest demonstration site as another observable state variable that directly enters profits, my implementation is more realistic. The owner of a cleaner either will or will not visit each demonstration site, depending on the distance to the demonstration site. The farther the demonstration site, the less likely an owner will be aware of it or able to make the trip, but the benefit from visiting should not not depend on the distance.

The probability that firm i takes action j at time t can now be expressed as the sum of the choice probabilities conditional on having visited or not visited a demonstration site, multiplied by the probability that the firm owner did or did not visit at least one demonstration site:

$$P(j_{it}|x_{it}, \psi_t, \beta_i) = P(j_{it}|x_{it}, \psi_t, s_{it} = 1, \beta_i)P^s_{it} + P(j_{it}|x_{it}, \psi_t, s_{it} = 0, \beta_i)(1 - P^s_{it}). \tag{9}$$

4.4 Estimation

I first estimate the model under the assumption of homogenous, myopic firms, i.e. I set the discount factor to $\rho = 0$ and $\beta_i = \beta$. Estimation proceeds using simple maximum likelihood estimation; I maximize the likelihood function over possible values of the profit function parameters. The estimation procedure is the same for the case of homogenous, forward-looking cleaners. In the case of forward-looking firms, I assume an annual discount factor of $\rho = 0.9$. Let a firm's observed actions at time t be given by Y_{it} and state by X_{it}. The likelihood of all cleaners' actions (incumbents and potential entrants) conditional on β can be expressed as:

$$L(Y_{it}|X_{it}, \beta) = \prod_{i=1}^{I} \prod_{t=1}^{T} P(Y_{it}|X_{it}, \psi_t, \beta), \tag{10}$$

where the capital letters indicate observed data and I is the total number of incumbent firms and potential entrants. I assume that in any year, there are 100 potential entrants, approximately 1/30 of the number of incumbent firms. I assume that these firms either enter the market or disappear, to replaced by 100 new potential entrants in the next year. The likelihood expression includes the probability that the new entrants enter and that one hundred minus the number of actual new entrants in each year choose to not enter the market, as well as the probabilities of all of the incumbents' actions. By including potential entrants in the likelihood function, I allow for the endogenous entry of cleaners in the model of technology adoption. The choice of the number of potential entrants will expect the estimate of the entry costs but should not appreciably affect the estimates of the other parameters.

When including firm heterogeneity, the likelihood of cleaner i's actions conditional on β_i is given by:

$$L_i(Y_{it}|X_{it}, \beta_i) = \prod_{t=1}^{T} P(Y_{it}|X_{it}, \psi_t, \beta_i). \tag{11}$$

To determine the unconditional likelihood of cleaner i, I need to integrate over the distribution of β_i for observed cleaners:

$$L_i(Y_{it}|X_{it}, \beta_i) = \int \prod_{t=1}^{T} P(Y_{it}|X_{it}, \psi_t, \beta) d\widehat{F}(\beta_i), \tag{12}$$

where $\widehat{F}(\beta_i)$ is the cummulative probability distribution of β_i.

Maximizing the simulated log likelihood function with standard numerical integration would involve drawing from the distribution of β_i and recomputing the value functions for all states and draws every iteration of the optimization process. To alleviate the computational burden, I instead use importance sampling as described in Ackerberg (2009). The insight of importance sampling is that it is only necessary to compute the value functions and individual likelihoods once, for each draw of the parameter vector. Instead of changing the simulation draws for each iteration of the optimization process, which are given equal weight in evaluating the integral using traditional numerical integration, I use the same set of draws throughout optimization and simply change the weights on each of the R draws by maximizing the likelihood function over the parameters of the distribution of β_i. The simulated likelihood takes the following form:

$$L_i(Y_{it}|X_{it}, \beta_i) = \sum_{r=1}^{R} \widehat{f}(\beta_r) \prod_{t=0}^{T} P(Y_{it}|X_{it}, \psi_t, \beta_r). \tag{13}$$

It is important to note that when including heterogeneity, there is an initial conditions problem which must be addressed. I assume that the distribution of β_i for potential garment cleaners follows a multivariate normal distribution:

$$\beta_i \sim N(Z_i\theta, \Sigma), \tag{14}$$

where θ and Σ are parameters to be estimated and Z_i includes exogenous, time-invariant demographic demand variables and firm variables which explain some of the heterogeneity. This distribution is not the same as the empirical distribution of parameters for firms in the data. It is necessary to control for sample selection: Cleaners with more favorable profit parameters are more likely to be in the data. The distribution $\widehat{f}(\beta_i)$ is equal to the probability that cleaner i has profit parameter vector β_i *and* is in the panel data at time $t = 0$, which is equal to the following:

$$\widehat{f}(\beta_i) = P(X_{i0}, \beta_i) = p(X_{i0}|\beta_i) f(\beta_i|Z_i\theta, \Sigma). \tag{15}$$

The traditional challenge in controlling for the initial conditions is the calculation of $p(X_{i0}|\beta_i)$. However, I can calculate the stationary probability distribution of the state variables at the start of my panel $p(X_{i0}|\beta_i)$ by iteratively multiplying the state transition matrix by itself until the solution converges, for every draw of β_r. The deterministic state transition matrix is equal to the state transition matrix conditional on the firm's actions multiplied by the probability of the firm's actions, which are conditional on the state X_{it} and parameter draw β_r:

$$\begin{aligned} \chi(x \longrightarrow x|\beta_r) : P(x'|x, \beta_r) &= P(x'|x, j) P(j|x, \beta_r), \\ P(x_{i0}|\beta_r) &= \chi^{\infty}. \end{aligned}$$

This method of calculating the initial conditions' stationary distribution is computationally feasible since it only has to be performed once for each draw β_r when using importance sampling.

For all of the firms in the data, the probability of the parameter draw is conditioned on the observables Z_i. One final complication is that I do not observe the values of the Z_i variables for the potential entrants who do not enter the market. I cannot use the distribution of incumbent cleaners since the Z_i values for the incumbent firms may not be representative of the population distribution; like with the draws of the β_i, cleaners with more favorable observable characteristics are more likely to have entered the market at some point and be in the data. Fortunately, from the Reference USA data, I have the values for the firms which do not have equipment permits and so must be outsourcing firms. I assume that the potential entrants who do not enter in each year have Z_i variables which are drawn from the empirical distribution of the outsourcing firms. I draw $R_p = 100$ values of Z_i from the outsourcing firms for the potential entrants. The probability of the draw of β_i for the potential entrants who do not enter is calculated by numerically integrating over these Z_i, $f(\beta_i) = \frac{1}{R_p} \sum_{r_p=1}^{R_p} f(\beta_i|Z_{r_p})$.

For notational convenience, I define $P(X_{i0}|\beta_i) = 1$ for those cleaners who are not present in the data set at the beginning of the panel. The likelihood of the data can be written as:

$$L = \prod_{i=1}^{I} \sum_{r=1}^{R} w_{ir} P(X_{i0}|\beta_r) \prod_{t=0}^{T} P(Y_{it}|X_{it}, \psi_t; \beta_r), \tag{16}$$

where the weights for each draw are the product of the probability of the draw multiplied by the probability that that draw would be present in the data prior to the beginning of the panel at $t = 0$, for those cleaners who are present at the beginning of the panel. The values of w are equal to the normalized ratio of the probability distribution functions $f(.)$ and the sampling distribution $f_0(.)$:

$$w_{ir} \propto \frac{f(\beta_r|Z_i\theta, \Sigma)}{f_0(\beta_r|\theta_0, \Sigma_0)}, \sum_{r=1}^{R} w_{ir} = 1. \tag{17}$$

I estimate the model by maximizing the log likelihood over the parameters θ and Σ using $R = 1000$. I use a normal distribution for the sampling distribution with the homogenous firm parameter estimates as the mean and the identity matrix multiplied by a scale factor of two as the covariance matrix. I then rerun the estimation using these parameter estimates as the parameters of the new sampling distribution, multiplying the variance matrix by a scale factor of three to ensure sufficient coverage of the parameter space.

4.5 Identification

Identification of the model parameters is dependent on what actions the cleaners have made in which states. As previously mentioned, I observe cleaners enter, make the choice to buy new equipment, operate using their existing equipment, or leave the market but there are no cleaners who adopt wet cleaning, carbon dioxide, or GreenEarth equipment who then exit the market or purchase new equipment in a later year.

The timing of firms exiting the market and purchasing new equipment allows me to identify the effect of equipment age on a firm's utility in each period both when using existing equipment and purchasing new equipment. In addition, I can identify utility intercepts for each type of technology I observe being purchased in the data. Before 2001, there are no observed purchases of wet, carbon dioxide, or GreenEarth cleaning equipment. In case I may not have included all green cleaners who adopted these technologies before 2001, and because I do not want to assume that cleaner awareness and beliefs regarding these technologies and the costs were the same before and after this date of first adoption, I include a large, negative utility intercept for these three green cleaning technologies before 2001. This allows me to use the data before 2001 in identifying most of the profit function coefficients, but only use the data in and after 2001 to identify the profit function intercepts for wet, carbon dioxide, and GreenEarth cleaning.

The inclusion of this disutility of using these types of equipment before 2001 means that to separately identify purchase and utilization intercepts, I would need to have observed firms with each type of equipment make subsequent purchase decisions in 2001 or later, which is not the case. To address this issue, I include observable average equipment costs for the different types of equipment. The coefficient on these costs is identified from the variation across technologies. I can also identify an equipment-independent purchase intercept, β_{iP}, using the fact that I can separately identify utilization and purchase utility for perc owners since I observe repeat purchases. The costs of entry coefficient is identified, after specifying a number of potential entrants each period, by the number that actually enter.

Identification of the perc fee coefficient is possible from the time-series variation in the perc fees, which begin at \$3 per gallon of perc in 2004 and increase annually by one dollar to a maximum of \$12 in 2013 (this was known to firms in 2003). I can get identification from the different behavior of firms in these years as well as the fact that there were no announced fees before 2003. Because the effect of the perc fees can be identified and they are measured in today's dollars, I can scale the parameter estimates so that firm profits are given in dollar amounts. Without this or similar variation, the profit function parameters are only identified with a normalization of the variance in the error term.

I can identify the added utility from visiting a demonstration site from the time series and cross-sectional variation in the state-dependent value functions when visiting and not visiting. Whether a firm has visited a demonstration site or not will lead to different values of the value function. Firms who are more likely to replace their equipment will be more likely to visit a demonstration site. Recall that the effect of a demonstration site enters in a discrete manner in the computation of the value functions, since a cleaner either does or does not visit a site. Because of this, I estimate two coefficients: the magnitude of the effect of visiting a demonstration site and the effect of distance to the demonstration sites on the probability of visiting.

The ability to identify the magnitude of the effect of demonstration sites would be possible even without geographic proximity being a factor becasue I observe adoption decisions before and after the entry of the first demonstration site. Determining the effect of geographic proximity is possible using the geographic variation in locations. However, since I am using a single moment condition to identify two coefficients, the scale of the second coefficient is not identified. Functional form is what allows me to identify both coefficients: the probability of visiting a demonstration site is constrained to be on the $[0, 1]$ interval, and the scaling is determined by my selection of the variance of η_{it}.

The identification of firm heterogeneity is possible due to the panel structure of the data, but it is aided by the changing regulations and incentives. With every policy change, the relative utilities of firm choices are changed, leading to different probabilities for each alternative. The choices different firms make as not only their states but their value functions change identify the distribution of heterogeneity. With inclusion of firm heterogeneity, I allow for and estimate the correlation between some of the profit function parameters. The policy changes also help to identify these correlations. For example, the large spike in perc purchases in 2007 implies that there is a sizeable fraction of firms who prefer perc so much more in comparison to the green alternatives that they are willing to purchase new equipment earlier than they would otherwise. The magnitude of this spike is what helps to identify the correlation of profits when using perc in comparison to the alternatives. However, not all correlations can be estimated.Becasue I do not observe wet cleaning firms also purchase carbon dioxide cleaning, I cannot estimate a correlation parameter for profits when using the two types of equipment. However, I do see firms with both perc and hydrocarbon equipment purchase the other technologies. If I assume that the correlation in profits when using the different types of green equipment is the same for all types of green equipment, the correlation in the profit parameters can be estimated from the choices of hydrocarbon cleaners who switch to the other green technologies.

Additional correlations I estimate include the correlation between the profit intercepts and the effect of the perc fees, as well as the equipment age coefficient and the effect of the perc fees. Identification is possible using cross sectional variation in how much firms are affected by the perc fees, ones with newer or older equipment, and their resulting purchase behavior. I can also estimate the correlation between the green equipment profit parameters and the demonstration site parameters by determining whether it is the firms with perc or hydrocarbon equipment which are more likely to visit and benefit from a demonstration site. While in theory these correlations would be identifiable from the variation in demonstration site locations, it is the changing relative values of the technology alternatives that result from the significant policy changes which allow for more precise estimation of these values.

5 Results

5.1 Homogenous Firm Estimates

I estimate the model with firm profits given in (3) for three alternative assumptions: the first assumption is that firms are myopic, the second is that firms are forward-looking and expect the incentives to be available only for the current year, and the third is that firms are forward-looking and expect the green equipment incentives to be available in future years. Using a chi-squared likelihood ratio test I can easily reject both the first two assumptions at 1% significance in favor of the third assumption: forward looking firms who assume that the green equipment purchase incentives are available in future years. I constrain the parameters on the fees and purchase costs to be positive so that their effect on profits must be negative by estimating the log of the parameter, since I know a priori that these costs should decrease profits.[18] I report the log values, so that a value of zero implies that these costs are scaled by a factor of one.

The estimation results are in Table 6 for the assumption of forward looking cleaners, both if they assume there are no future grants and if they do. The results are similar except for the

[18]The results are robust to the non-restricted case, although with the inclusion of heterogeneity, outlying draws of β_i would imply benefits from increasing costs without the constraint.

effect of a demonstration site which is estimated to be more than half again as large under the assumption of future incentives. The following discussion applies to the second column estimates under the assumption of future grants. In addition to the estimated values whose scale depends on the normalization of the error term, I include the monetary equivalents for the coefficients where appropriate, which are calculated by scaling the coefficient on the changing perc fees to be equal to one.

All of the coefficients are significant at 1% except for the distance to the demonstration sites, which is of the expected sign. Unexpectedly, the age coefficient is positive and almost equal to zero. However, this does not mean that profits increase with age, since the effect of age is relative to the scrap value of exiting the market. The coefficient estimate of approximately zero indicates that the effect of equipment age is approximately the same when using old equipment or when buying new equipment or exiting the market, which I would expect if there was an efficient secondary market for equipment.

The relative profits when using the different types of equipment are not surprising given the overall adoption of the different types of technology and the differences in equipment costs. Profits are highest when using perc and hydrocarbon equipment, the closest perc substitute. These are followed by GreenEarth and carbon dioxide equipment, and wet cleaning is by far the least profitable. This is not surprising given the data; the lack of widespread adoption of wet cleaning, considering there may actually be cost benefits, points to industry sceptism. Although the CAARB has conducted efficacy tests for wet cleaning and found that over 99.5 percent of the garments that are usually dry cleaned are able to be wet cleaned, this does not mean that the owners of cleaning establishments are convinced that wet cleaning is a sufficient substitute for traditional dry cleaning. Individuals in the industry I have spoken with have conveyed doubt regarding the efficacy of wet cleaning, and cleaners using wet cleaning will often outsource some garments to traditional perc facilities. However, if the firm has visited a demonstration site, the added value from the visit actually increases the profitability when using wet cleaning to be much more comparable to GreenEarth and carbon dioxide. The effect of distance to the demonstration sites, as expected, decreases the value of visiting.

The relative sizes of the coefficients on the purchase costs and the perc fees give me an idea of how important the two are. Differences in equipment costs have only 40% the effect that the perc fees have on purchase probabilities. This is likely due to the fact that in actuality, firms can finance their equipment costs. The ability to delay payment of the equipment purchase costs should not affect the other parameter estimates in a meaningful way but will lead to different coefficients on the perc fees and the equipment costs, which otherwise should be the same.

When using the homogenous coefficient estimates to calculate the probability of the different cleaner actions in each year, some of the peculiarities of the data are are not well explained. In particular, the 2007 policy change to prevent perc purchases after that year increases the probability that a perc firm buys new perc equipment the last time it is available in 2007, but only marginally (The same is true for firm exit in 2003 and 2007). What I have not yet accounted for is firm heterogeneity; if some firms value perc cleaning much more than the alternatives, the policy change would lead them to buy perc equipment in 2007 even if they would have waited without the policy change. With the inclusion of firm heterogeneity, firms will be affected by the changing policies by dramatically different amounts, which will be reflected in a greater aggregate response to the changing incentives and regulations.

5.2 Heterogeneous Firm Estimates

As described earlier, firm heterogeneity is included with the use of importance sampling, where I draw the parameters from a multivariate normal distribution. I estimate the mean and covariance matrix of the multivariate normal distribution from which the parameters are drawn. Again, I constrain the coefficients on the equipment purchase costs and perc fees to be positive by estimating the log of the parameter, which leads to a negative effect of fees and purchase costs on profits. This constraint with the inclusion of heterogenous parameters is equivalent to assuming a log-normal distribution for these two parameters.

I do not allow for a fully flexible covariance matrix which would not be identified, although I do estimate certain elements of the covariance matrix in a coherent manner. In addition to the diagonal elements of the covariance matrix, I estimate the correlation between some of the key profit parameters which I believe a priori might be related. In the estimation procedure, if I estimate a correlation between one parameter and several other variables, I include all of the implied correlations for these other variables. For example, I estimate the correlation between the green equipment profit parameters and the utility derived from visiting a demonstration site, setting this to be the same for all green equipment types. This correlation then naturally implies correlation between the green equipment parameters with each other. The non-diagonal elements of the covariance matrix depend on the estimated correlations as well as the estimated diagonal elements of the covariance matrix.

The parameters are estimated under the assumption that firms expect the green technology incentives to be present for the current and future years. I estimate the model under the alternative assumption that the cleaners assume the grants will be available only in the current year, but this assumption is rejected with a likelihood ratio test. The estimation results can be found in Table 7. In my base result, I do not include firm and market variables in the expression for the mean of the distribution of the parameters, i.e. Z_i includes only an intercept, although I do include them later. Again, I include the monetary equivalent for the estimated coefficients in the table by dividing by the average effect of the perc fees.

As with the estimates using homogenous cleaners, I find that there is not a large average effect of equipment age on profits when using existing equipment or purchasing new equipment, relative to the scrap value when exiting the market. The purchase intercept and barrier to entry intercept are negative as expected, although the barrier to entry is estimated imprecisely. There is limited interpretability of this parameter since it is identifiable only by specifying a priori the number of potential entrants.

Perc cleaning is considered the most profitable technology by cleaning firms on average. However, although the average profits are largest when using perc cleaning, for a subset of firms, perc cleaning may not be the most profitable option. It is these cleaners who are more likely to adopt one of the new technologies. Wet cleaning is the least profitable type of cleaning on average if the cleaners' owner has not visited a demonstration site, but there is lots of heterogeneity in the profit intercept, more so than for the other types of cleaning. In addition, the benefit from visiting a demonstration site also exhibits considerable heterogeneity, and the average benefit from attending a demonstration makes wet cleaning about as profitable as carbon dioxide and GreenEarth cleaning. These results means that there is a non-negligible subset of firms who would actually prefer wet cleaning after having visited a demonstration site.

The coefficient on the perc fees can be interpreted as the average annual volume of clothes cleaned (up to a scale parameter) since the perc fees are are per-volume fee, so long as the solvent costs are the same across firms. Variance in this parameter would then be caused by variance in the volume of clothes cleaned by different firms. This means I can use the correlation between the equipment-specific intercepts and the fee coefficient to disentangle firm variable and fixed profits. If the correlation is large, then firm profits are mostly variable profits, whereas the opposite is true if the correlation is small.[19] Table 8 shows the estimated correlations for different parameters in column 3. The total estimated correlations between the parameters, inclusive of the implied correlations, is in the fourth column of the table.

As expected, there is positive, significant correlation between the perc fee coefficient and firm profits using perc or green equipment. This is as expected, since in general I would expect that firms which clean more clothes per year would be more profitable. In addition, I would expect the effect of equipment age to be negatively correlated with the perc fee coefficient since the volume of clothes cleaned should lead to more machine depreciation when using old equipment, and I find that this is in fact the case. There is a positive correlation between the green equipment profit intercepts and both the probability of visiting a demonstration site and the benefits from the visit (conditional on visiting), again, not surprising if firms that believe the alternative technologies are more profitable are more likely to seek out and benefit from the information and training available at the sites. The hypothesis that a subset of cleaners are more profitable using perc relative to using the other technologies is confirmed by the estimated correlation of cleaners' profit parameters for the different equipment types. There is a negative correlation in profits when using perc and the other types of equipment of -0.23 (not including the implied correlations from the other profit parameters), which helps to explain the spike in perc purchases in 2007. There is a negligible,

[19]This statement depends on the assumption of a homoscedastic error.

positive correlation in profits when using the different types of green technologies (again, not including the implied correlations from the other profit parameters).

These findings have important implications for policymakers' abilities to phase out the use of perc without strict command-and-control legislation. If a subset of cleaners are unwilling to switch to one of the alternative technologies even with large monetary incentives, then command-and-control legislation may be necessary to force them to switch. On the other hand, such regulation could instead drive these firms out of the market, since exit may be preferred to operating using one of the alternative technologies. In addition, it may be the case that there is significant over-subsidization for another subset of firms who would have adopted the new technologies even without the incentives.

The large amount of heterogeneity is hardly surprising. It is reasonable to expect that different firms would make different profits using different types of equipment. Accounting for this heterogeneity is crucial in accurately forecasting the adoption of the perc alternatives. To try to explain some of the heterogeneity in firm profits, I estimate the model including firm variables such as credit rating, sales, and square footage available from the Reference USA data, as well as market demographic variables. The zip-code level demographic variables are intended to capture consumer demand shifters for garment cleaning, or environmentally-friendly cleaning specifically, and include median income, average household size, the fraction of vehicles registrations from 2001-2008 which are hybrids, and the fraction of the population who are male, white, aged 20-44, aged 45-64, unemployed, have a college degree, and use clean transit to commute to work. In general the coefficient estimates are not significant for any of these variables in explaining the heterogeneity in firms' profit parameters.

5.3 Robustness Checks

In including the structure necessary to estimate the model primitives, several assumptions were made. The first assumption regarded cleaners' expectations regarding the availability of future equipment grants. I found that the assumption that firms do not expect future grants to be rejected for the assumption that they assume grants will be available in future years using a likelihood ratio test. In addition, I assumed a particular value of the annual discount rate, 0.9, a value often used in the literature. As robustness checks, I estimated the model using a range of values from 0.75 to 0.95, with similar results. The coefficient that was affected the most was the profits for carbon dioxide cleaning, not surprising considering the high, up-front capital costs. The more the cleaners discount future profits (lower ρ) the higher the profits necessary for carbon dioxide cleaning to justify the large capital expense. In addition to trying different values of the discount factor, I estimated the model while estimating a heterogeneous discount factor for cleaners. The policy changes which lead to variation in the value functions for firms over time can be used to identify the discount rate. Not surprisingly, I find the average discount rate is around 0.9.

Another key assumption was the scaling of the error term in the model of demonstration site visitation. I estimated the model using a range of values with similar results. I also used different reduced form specifications for the probability of visiting a demonstration site that did not depend on the state variables, including a linear and exponential probability function and a discrete cutoff distance. In all cases, there was a positive benefit of the demonstration site which declined with distance to the site.

An assumption needed to estimate the entry costs was the number of potential entrants. While changing the number of potential entrants does lead to different estimates of the entry costs, the other parameter estimates are largely unchanged. As previously mentioned, I did use more flexible specifications for the effect of equipment age as well, but found that the estimated coefficients led to a function similarly shaped to the concave logarithmic function. While in theory it is possible to allow the effect of equipment age of the existing equipment to enter when purchasing new equipment, I found the estimated coefficient to be imprecisely estimated and close to zero, indicating that any age-dependent scrap value for the old equipment when purchasing new equipment is about the same as when exiting the market.

One potential concern is the possible endogeneity of the demonstration sites. For this to be an issue, cleaners electing to be demonstration sites would need to be unproportionately represented in areas where cleaners are more likely to purchase green equipment. I do find correlation in the green profit parameters and the effect of distance on the probability of visiting a site, but no correlation between the green profit parameters and the effect of visiting. If there is endogeneity of the locations, this would impact the estimate of the effect of distance to the sites, but should not significantly impact the parameter measuring the effect of the sites which is primarily identified using the period before and after there were any sites, or the other parameters. Allowing heterogeneity in the parameters will also help mitigate bias from endogeneity since the effect of distance to the demonstration sites are cleaner-specific.

In case endogenity of demonstration sites is still a concern, I estimated the base model with heterogeneity using fit values of the distances to demonstration sites variables, regressing the distances on exogenous instruments. For instruments, I used a dummy variable indicating if the zip code is a low-income, cancer risk area where there was extra effort to get cleaners to become demonstration sites, as well as the number of total dry cleaners within a 5 kilometer radius, since most demonstration sites are cleaners and a high number of nearby cleaners increases the probability of one becoming a demonstration site. While one could anticipate cleaners being reluctant to share the information with their competitors, I have found that cleaners actually welcome the chance to share their knowledge by speaking at educational meetings, and they are compensated for becoming a demonstration site. The results using the fitted distance variable are similar to those using the actual distances for the other coefficient values.

In order to test for the suitability of a single agent model, I compare the number of cleaners and green cleaners who are nearby entering and exiting firms. Not unexpectedly, cleaners are more likely to enter in regions with a lower concentration of firms than the areas with exiting firms. However, the distinction between perc and non-perc cleaners does not appear to be important, since the fraction of nearby cleaners who are green are similar for entering and exiting firms. Also, it does not appear that the geographic proximity of other cleaners has a large effect on the adoption decisions. On the other hand, geographic proximity of demonstration sites does help explain which cleaners have adopted wet cleaning since these cleaners are on average closer to a demonstration site than those who have not adopted these technologies. I have confirmed these findings using a descriptive logit model where the regressors include the number of nearby firms, the equipment age, the distance to the nearest demonstration site, and dummy variables for year, county, and the cleaners' current type of equipment. There does not appear to be any systematic effect of nearby firms on the utility of adopting the green types of equipment.

6 Discussion

Because of both the durable nature of the equipment and the changing incentives and regulations, it is necessary to account for possible state dependence in cleaners' adoption decisions, both on current equipment type and age, as well as on the current year. As expected, the static model is easily rejected with a likelihood ratio test, as is the model under the assumption of green equipment grants for the current year only. The value functions for cleaners vary considerably as new incentives are added, the perc fee increases, and as the industry moves closer to the mandatory perc phase-out date.

Although I find that the average effect of equipment age does not factor into firms' profits relative to the scrap value, there is heterogeneity in the age parameter which is positively correlated with the parameter on the per volume perc fees, which captures the heterogeneity in the volume of clothes cleaned. Cleaners which are more affected by the fees and therefore likely clean a higher volume of clothes per year are more likely to have profits decrease with equipment age relative to the scrap value, due to machine depreciation.

In addition, I find that cleaners' profits when using perc equipment are negatively correlated with profits using the alternative technologies, a finding that results in higher costs for firms who prefer perc significantly over the alternatives, and may imply over-subsidization of the green equipment types since some firms would have adopted the new technologies anyway. There is a large effect of the demonstration sites in increasing cleaner profits when using wet cleaning which varies considerably by cleaner, and the probability of visiting a demonstration site is correlated with the profits when using the green technologies and decreases with distance to the demonstration site. Not surprisingly, New York and Massachusetts are also implementing demonstration site programs to help increase adoption of green cleaning technologies.

In addition to the effectiveness of the demonstration sites, I find that the effect of the perc fees is significantly larger than that of the equipment purchase grants, possibly since the equipment can be financed. Not only should the manufacturers of the alternative technologies supply information and training to garment cleaners, they may also want to subsidize the alternative solvents, even if this means that the equipment costs would be higher.[20]

The heterogeneity in the profit parameters can be explained either through cost differences, volume heterogeneity, or through prices. It may be the case that garment cleaning firms have the ability to differentiate themselves along an environmental dimension. One limitation of the model used in this paper is that it does not account for strategic behavior by firms in the timing of adoption of new technologies. However, descriptive regressions do not find any evidence that firms are strategic in their adoption decisions; if they are, then it is a second order effect. This is not surprising, since the policies in California have been changing so much that cleaners are having enough trouble keeping current on the restrictions and incentives. In talking with the owners of cleaning establishments and from questions posed at a cleaning information session sponsored by the San Francisco Department of the Environment, owners were far more interested and worried about constantly changing and unanticipated regulations, and the efficacy of the new technologies than they were about how consumers would react to the use of the new technologies.

That being said, there may still be a significant portion of consumers who would be willing to pay for cleaner technologies. Unfortunately, although there has been a great deal of effort to educate the owners of cleaning establishments about the perc cleaning alternatives, consumers for the most part are not informed about these alternatives and there is no control or oversight regarding environmental claims by cleaners. Some cleaners do change their names after purchasing one of the cleaner technologies, and the word ”organic” appears often in the windows of cleaners, but it is a meaningless term. All organic means in the context of garment cleaning is that carbon-based chemicals are used, which include perc. Because there is little consumer education and no oversight in environmental claims, it is up to the consumer to figure out which cleaners actually use

[20]There is evidence that equipment manufacturers are trying to help provide the information to cleaners from their presence at informational sessions on the use of the new technologies sponsored by the different air quality management districts in the state and by the CAARB, along with the San Francisco Department of the Environment and other local organizations.

environmentally friendly technologies.

Although I do not believe that California firms are behaving strategically in their adoption decisions, this would not necessarily be the case if there was more certainty in the future regulations as well as consumer education and oversight in the environmental claims made by cleaners. The primary reason for a lack of strategic behavior may simply be because the current system makes it very hard for firms using the clean technologies to convey that information to consumers. The Green Cleaning Council was recently established in 2008, with the help of the National Cleaners Association, to help provide information to consumers and to provide an environmental rating system for garment cleaners. This may help, but the rating system is voluntary and relies on the statements made by individual businesses. A reliable, non-voluntary third party verification and rating system could help allow consumers to make educated choices between cleaners based on their environmental commitment, which could be an alternative way to increase green technology adoption without relying solely on grants, fees and restrictions.

7 Counterfactual Analysis

While California's policies are designed to both phase out perc and favor carbon dioxide and wet-cleaning, the state of Oregon is simply trying to reduce the use of perc cleaning equipment. Unlike in California, in Oregon there are no grants for the purchase of the alternative types of equipment. In this section I use the heterogenous profit estimates to perform market simulations in order to predict the future state of the southern California garment cleaning industry under the Oregon policy as well as under no policy. I do this with and without firms receiving the benefits from the demonstration sites. Interestingly, while the California cleaners opposed additional regulation, in Oregon, the legislation was actually proposed by the garment cleaning industry. This was because cleaners were thus able to avoid individual liability under Oregon's cleanup law, which requires responsible parties to pay for cleaning up contaminated property.

In 1995, the Oregon Legislature passed Oregon's Dry Cleaner Statute, House Bill 3216 (ORS 465.500). The Dry Cleaner Statute requires all dry cleaners to implement waste minimization and hazardous waste management practices designed to eliminate future releases of hazardous waste to the environment – the solvents used are heavier than water and can easily get into the ground. In return, individual dry cleaners who pay fees will not be liable under Oregon law for the cost of cleaning up a site contaminated due to past practices. Since January 1, 1996, dry cleaners have been paying a ten dollar per gallon fee on the use or perc and a two dollar per gallon fee on the use of any other solvent to support the cleanup program.[21]

As shown in Figure 1(a) and 1(b), I find that both the Oregon and California policies will induce firms to purchase more hydrocarbon or GreenEarth cleaning equipment than no policy.[22] Until 2007, when California announced that firms would no longer be able to purchase perc equipment after that year, the expected levels of adoption of hydrocarbon or GreenEarth equipment under the two policies were about the same, so the distant ban on perc in California with the lower perc fees have a comparable effect to the higher perc fees and alternative solvent fees in Oregon. However, after this year, the predicted adoption of hydrocarbon equipment continues to increase under the California policy as firms' perc equipment becomes unusable, either from breakdown or because the equipment reaches 15 years of age. Under the Oregon policy, the rate of hydrocarbon and GreenEarth adoption decreases considerably.

Without the demonstration sites, under either policy or no policy, there is limited adoption of the technologies considered to be the cleanest: wet and carbon dioxide. However, with the information and training provided by the demonstration sites, I find that the expected fraction of firms which adopt wet or carbon dioxide equipment by 2021 to increase from almost zero adoption to almost 15%, under the California policy. Even with no perc fees or green equipment incentives, I find that the demonstration sites will lead to considerably more adoption of these two technologies.

Unfortunately, while the demonstration sites may lead to much more adoption of wet cleaning, the overall level of adoption for all of the green technologies is not affected to the same degree

[21] All cleaners who used any solvents prior to January 1998 also had to pay a one-time fee of $500.

[22] It must be noted that in the California data, I do observe firms after 2003 with perc equipment older than 15 years old, which cannot be used. In my simulations, I force these firms to either purchase new equipment or exit the market. I also run the simulations allowing them to remain in the market (either as inactive or outsourcing firms), and the results are qualitatively the same.

since many of the firms which would purchase wet cleaning are those that would have purchased hydrocarbon or GreenEarth cleaning equipment without the demonstration sites. In Figures 2(a) and 2(b), I show the fraction of firms owning perc equipment in each year under the different policies. The demonstration sites have little effect on the final fraction of firms using perc under the Oregon policy or under no policy, and of course under the California policy, all firms eventually must discontinue the use of perc.

Although both the California and Oregon policies have the ability to increase the level of overall green technology adoption, the policies come with different costs. The perc fees obviously increase firms' costs, and the fees are higher in Oregon. The green technology incentives in California may offset these costs for firms, but must be paid for with taxpayer money (and with the perc fees). Although there are higher perc fees in Oregon, firms still have the option to continue to use perc if they are willing to pay the fees. Figure 3(a) shows the extent of firm exit under the different policies. Interestingly, while the amount of exit is initially higher under the California policies, by 2009 it decreases below that predicted under Oregon's policies and by the phase out, around that of no policy. That being said, the reduced amount of exit by 2021 is offset by reduced entry under the California policy as shown in Figure 3(b). The tradeoff between the policies is clear: the higher marginal costs in Oregon due to the large perc fees and the fees on the other solvents leads to more exit of cleaners over time. However, the restriction against entry of new perc cleaners, even if they would be profitable with the large fees, is forbidden under the California policy leading to less overall entry. The net effect of entry and exit is a small increase in the number of firms under no policy (expected due to the new available technologies which increase the profits for some firms), almost no effect under the California policy, and small decrease in the number of firms under the Oregon policy. The costs of the California policy are of course higher than the Oregon policy: In addition to costs imposed on firms, less revenue is generated by the fees than in Oregon and there are the costs of the green equipment as well.

Finally, Figure 4 shows how the average age of the perc equipment being used changes under the different policies. This is important because older machines tend to pollute more. The California policy leads to the use of younger perc equipment initially since perc equipment older than 15 years old cannot be used in or after 2003, and from the spike in perc purchases in 2007.

However, these cleaners are likely to use this perc equipment until the phase-out, so while the number of perc machines being used is lower under the California policies, the average age of the perc equipment continues to increase.

8 Concluding Remarks

Using a dynamic, structural model of durable good replacement for garment cleaning firms in southern California, I am able to estimate policy-invariant profit parameters. The model controls for and exploits changing legislation to decompose profits and measure the impact of fees and incentives on green equipment purchases. In addition, I use the changing proximity of wet cleaning demonstration sites to measure the value of information and training for a new technology whose efficacy is uncertain.

I find that firm heterogeneity is important in explaining key characteristics of the data, and so must be accounted for in estimation. I estimate cleaners' heterogenous profit parameters using importance sampling, controlling for the initial market conditions by calculating the stationary equilibrium for the market before any of the policies are enacted for each draw of the profit parameter vector. In addition, I estimate significant correlation in many of the profit function parameters. The correlation between the perc fee coefficient and the equipment profit intercepts is larger for perc cleaning, providing evidence that profits are more variable in nature for perc cleaning. I find a large correlation in the effect of equipment age and the perc fees, leading me to conclude that machine depreciation increases with volume of clothes cleaned. Finally, there is a negative correlation between the profits using perc equipment and green equipment which has implications for both the effectiveness and the costs of the grants, fees and command-and-control regulations.

I find that both the California and Oregon policies will help increase and expedite the adoption of green technologies. The demonstration sites have a great effect in increasing the adoption of wet cleaning, but overall green technology adoption is affected only a little since it is the cleaners adopting the other alternative technologies who are likely to adopt wet cleaning. One limitation of the analysis is that I do not include outsourcing firms in the analysis, and I do not explicitly model the choice to outsource.[23]

Although there is a comparable amount of exit under the Oregon and California policies, there is far less entry of new cleaners under the California regulations. The welfare effect of this reduction in the total number of cleaners will depend on the transportation costs of consumers and the effect on cleaners' decisions to outsource. The impact may be mitigated some if consumers receive higher utility for environmentally friendly cleaning. With adoption and entry/exit decision only, I cannot separate revenues and costs and so cannot determine whether consumers are willing to pay more for environmentally friendly cleaning. One potential area of future research would be to study consumers' willingness to pay for green services such as garment cleaning, and whether this willingness to pay would increase with better control over environmental claims made by firms.

By structurally modeling firms' technology adoption decisions under unanticipated regulation changes, I am able to exploit an exogenous source of variation in estimating heterogenous profit parameters and perform counterfactual analyses. I conclude that the command-and-control regulations are needed to phase out the use of perc, especially considering the firm heterogeneity in profits using the different types of equipment. These regulations also lead to more firm exit, although whether that has positive or negative welfare consequences depends on the tradeoff between the environmental benefits and the costs to firms and consumers from the policies.

This is just one of many potential applications in which the adoption of a new technology or technologies may provide some social benefit but adoption is slowed due to the state dependence of the adoption decision. The approach allows me to incorporate the heterogeneity one would expect in utility for the new technologies while controlling for the endogeneity of the initial market conditions. It allows for the tractable estimation of a dynamic model when two-stage estimation is not feasible, in this case due to the heterogeneity and the non-stationarity of firms' value functions as a result of changing incentives and regulations, variation which allows for more precise estimation of the heterogeneity in the first place.

[23]Nevertheless, I do not take the strong position requiring firms to exit or purchase new equipment after 2003 when their perc equipment is 15 years old, allowing them to remain in the market in some capacity.

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Table 1: Cleaning Equipment Costs

Machine Solvent Type	Machine Cost	Operating Costs
Perc-Secondary Control (40-lb capacity)	$43,900	$15,000
Hydrocarbon (50-lb capacity)	$61,000	$10,500
GreenEarth (50-lb capacity)	$63,000	$14,500
CO2 (60-lb capacity)	$140,000	$8,800
Wet Cleaning (25-35 lb capacity)	$40,000	$9,600

Table taken from the California Air Resources Board Dry Cleaning Industry Technical Assessment Report, (Fong et al. 2006). Average operating costs include solvent, detergent/spotting agents, electricity, average maintenance, filters/gaskets, waste disposal.

Table 2: 2008 Cleaners

Equipment	Freq.	Percent	Distance to Nearest Demo Site
perc	1,920	61.84	17.90543
hydrocarbon	1,051	33.85	18.98943
wet cleaning	105	3.38	16.08161
carbon dioxide	4	0.13	13.40126
GreenEarth	25	0.81	21.04997
Total	3,105	100.00	

Table 3: Garment Cleaner Actions by Current Equipment Type, Percentages

Current Equip	exit	nothing	perc	h-c	wet	CO2	GE	N
perc	1.63	88.70	5.55	3.63	0.39	0.01	0.09	27,418
hydrocarbon	0.14	90.33	0.68	8.70	0.11	0.03	0.00	3,528
wet cleaning	0.00	97.91	0.42	1.67	0.00	0.00	0.00	239
carbon dioxide	0.00	100.00	0.00	0.00	0.00	0.00	0.00	16
GreenEarth	0.00	98.86	0.00	1.14	0.00	0.00	0.00	88
Total	1.44	88.99	4.94	4.18	0.35	0.01	0.08	31,289

Table 4: Garment Cleaner Actions by Current Equipment Age, Percentages

Current Equip	exit	nothing	perc	h-c	wet	CO2	GE	N
<3 years	0.59	85.59	5.74	7.53	0.46	0.03	0.07	7,410
3-6 years	1.45	89.15	6.30	2.71	0.37	0.00	0.02	4,828
7-9 years	1.68	89.36	5.86	2.63	0.32	0.02	0.13	4,748
10-12 years	1.41	90.53	4.47	3.28	0.23	0.02	0.06	4,762
13-15 years	1.47	90.69	3.51	3.82	0.35	0.00	0.16	4,298
16-18 years	2.08	90.75	3.81	2.98	0.32	0.00	0.06	3,125
18-21 years	2.14	90.97	2.86	3.51	0.39	0.00	0.13	1,539
>21 years	5.01	88.26	2.07	4.49	0.17	0.00	0.00	579
Total	1.44	88.99	4.94	4.18	0.35	0.01	0.08	31,289

Table 5: Garment Cleaner Actions by Year, Percentages

Year	exit	nothing	perc	h-c	wet	CO2	GE	N
1999	1.52	94.77	3.46	0.26	0.00	0.00	0.00	3,096
2000	1.99	90.97	6.59	0.45	0.00	0.00	0.00	3,113
2001	1.22	92.33	6.25	0.16	0.00	0.00	0.03	3,104
2002	1.31	90.55	6.00	2.08	0.06	0.00	0.00	3,131
2003	1.56	90.21	2.93	4.56	0.35	0.06	0.32	3,136
2004	1.46	90.48	2.13	5.00	0.73	0.00	0.19	3,142
2005	1.33	89.99	2.09	6.08	0.41	0.06	0.03	3,157
2006	1.43	88.65	1.71	7.93	0.22	0.00	0.06	3,153
2007	1.87	66.53	18.18	12.21	1.08	0.00	0.13	3,152
2008	0.71	95.75	0.00	2.83	0.64	0.00	0.06	3,105
Total	1.44	88.99	4.94	4.18	0.35	0.01	0.08	31,289

Table 6: Profit Function Estimates with Homogeneous, Forward-Looking Cleaners

	No future grants			With future grants		
Variable	estimate	std. err.	monetized	estimate	std. err.	monetized
age (β_w)	0.085	(0.009)	\$ 3,410	0.046	(0.009)	\$ 2,850
perc (β_2)	-0.107	(0.008)	\$ -4,290	-0.108	(0.008)	\$ -6,720
hydrocarbon (β_3)	-0.163	(0.010)	\$ -6,540	-0.171	(0.009)	\$ -10,640
GreenEarth (β_6)	-0.853	(0.053)	\$ -34,240	-1.016	(0.060)	\$ -63,220
carbon dioxide (β_5)	-1.134	(0.220)	\$ -45,520	-1.041	(0.001)	\$ -64,730
wet cleaning (β_4)	-2.338	(0.604)	\$ -93,840	-2.704	(0.189)	\$ -168,210
demo visit (β_s)	1.126	(0.601)	\$ 45,190	1.979	(0.175)	\$ 123,070
purchase intercept (β_P)	-2.316	(0.165)	\$ -92,950	-2.520	(0.108)	\$ -156,760
capital costs(log(β_K))	-1.390	(0.119)		-1.828	(0.117)	
perc fee (log(β_f))	0.981	(0.100)		1.263	(0.082)	
barrier to entry (β_B)	-1.843	(0.083)	\$ -73,980	-1.857	(0.084)	\$ -115,480
demo distance (β_d)	-1.381	(0.779)		-1.155	(0.538)	
log likelihood		-14,314.6			-14,175.5	

Standard Errors in Parentheses.

Table 7: Profit Function Estimates with Heterogeneous Forward-Looking Cleaners

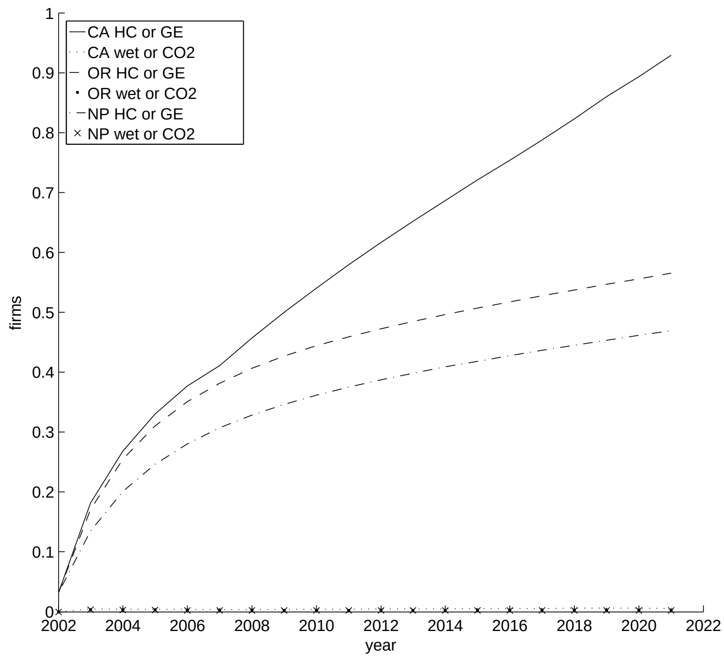
	Parameter distrib. mean			Parameter distrib. std. dev.		
Variable	estimate	std. err.	monetized	estimate	std. err.	monetized
age (β_w)	0.162	(0.056)	\$ 530	0.210	(0.021)	\$ 1,810
perc (β_2)	-0.084	(0.064)	\$ -270	0.371	(0.002)	\$ 3,200
hydrocarbon (β_3)	-0.164	(0.032)	\$ -530	0.222	(0.001)	\$ 1,910
GreenEarth (β_6)	-0.803	(0.032)	\$ -2,600	0.228	(0.019)	\$ 1,960
carbon dioxide (β_5)	-1.079	(0.019)	\$ -3,500	0.269	(0.001)	\$ 2,320
wet cleaning (β_4)	-2.276	(0.072)	\$ -7,380	0.508	(0.008)	\$ 4,380
demo visit (β_s)	0.987	(0.099)	\$ 3,200	0.532	(0.000)	\$ 4,590
purchase intercept (β_P)	-2.545	(0.011)	\$ -8,250	0.256	(0.001)	\$ 2,200
capital costs(log(β_K))	-1.440	(0.005)		0.220	(0.000)	
perc fee (log(β_f))	1.127	(0.003)		0.149	(0.006)	
barrier to entry (β_B)	-1.954	(0.021)	\$ -6,330	0.239	(0.005)	\$ 2,060
demo distance (β_d)	-1.466	(0.774)		0.758	(0.178)	
log likelihood			-58,125.7			

Standard Errors in Parentheses.

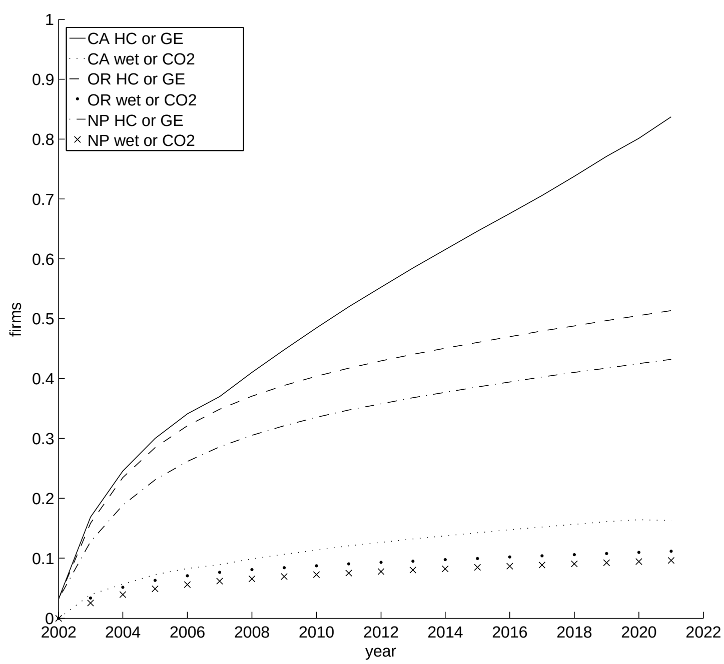
Table 8: Estimated Parameter Correlation with Heterogeneous Forward-Looking Cleaners

Variable 1	Variable 2	Contribution to Correlation	Total Correlation
perc fee	green equipment	0.312 (0.021)	0.312
perc fee	perc equipment	0.207 (0.031)	0.207
perc fee	age	-0.394 (0.147)	-0.394
green equipment	prob. of demo visit	0.147 (0.007)	0.147
green equipment	wet utility from demo visit	0.175 (0.004)	0.175
perc equipment	green equipment	-0.225 (0.034)	-0.161
green equipment	green equipment	0.031 (0.018)	0.231

Standard Errors in Parentheses.

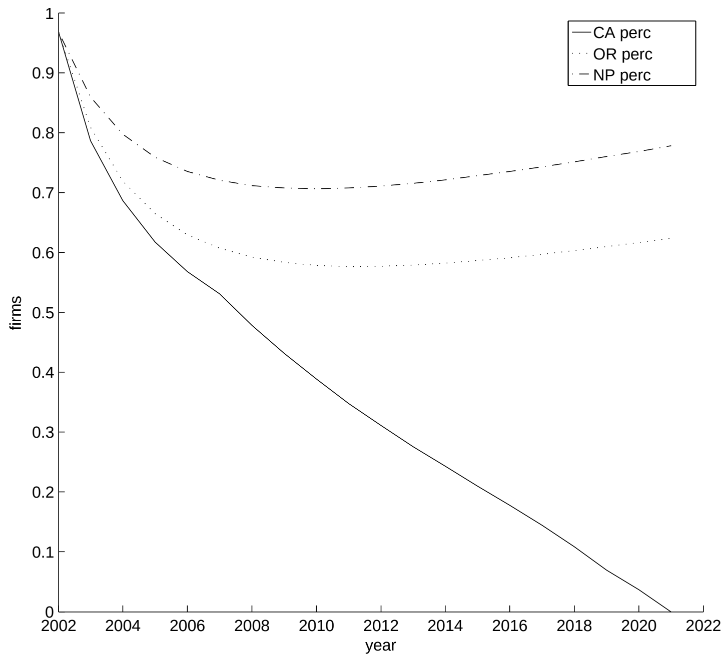


(a) Without demonstration sites

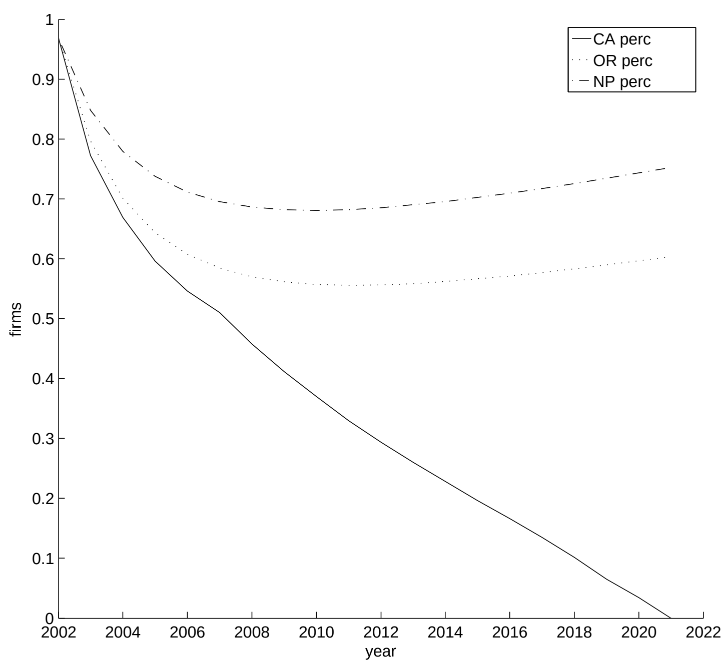


(b) With demonstration sites

Figure 1: Number of cleaners owning green equipment as fraction of initial number of cleaners

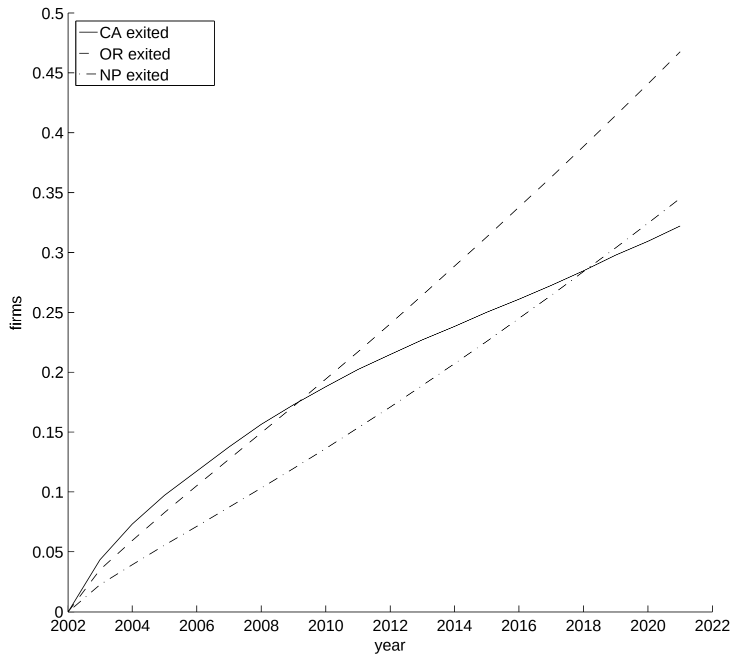


(a) Without demonstration sites

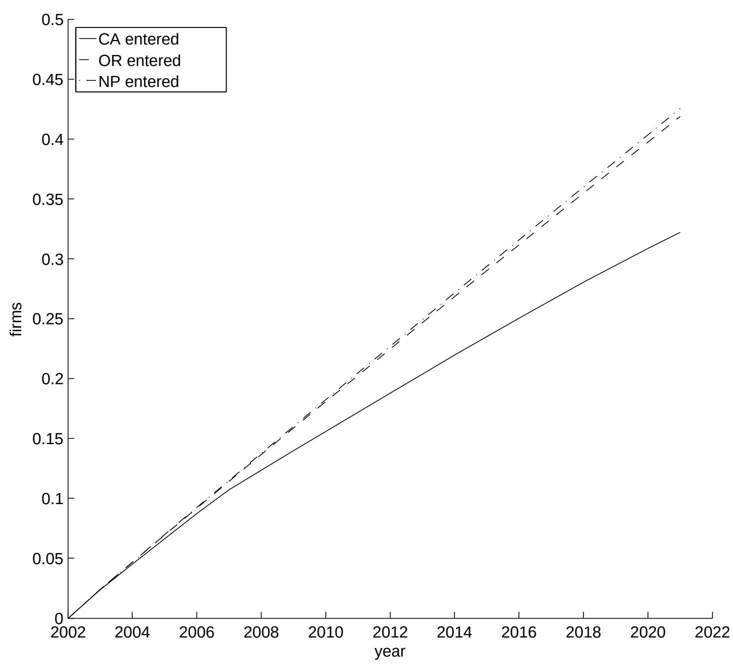


(b) With demonstration sites

Figure 2: Number of cleaners owning perc equipment as fraction of initial number of cleaners



(a) Firm exit



(b) Firm entry

Figure 3: Number of firms that exit (a) and enter (b) with demonstration sites as fraction of initial number of cleaners

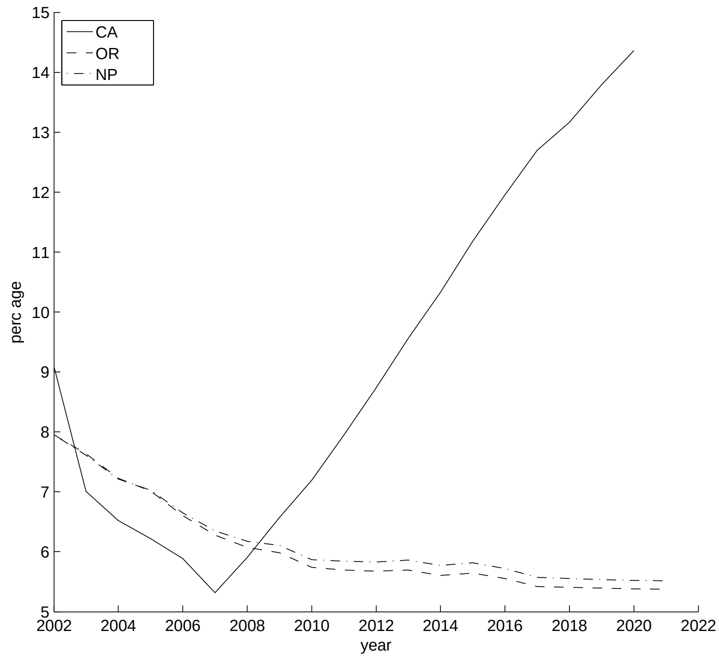


Figure 4: Average age for cleaner perc equipment in each year