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# Who Signed Up for the Do-Not-Call List?\*

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“The makers of our Constitution . . . sought to protect Americans in their beliefs, their thoughts, their emotions and their sensations. They conferred as against the Government, the right to be let alone—the most comprehensive of the rights of man and the right most valued by civilized men.”

— U.S. Supreme Court Justice Louis D. Brandeis.

## Abstract

This paper uses the results of a natural experiment to assess consumer demand for a particular kind of privacy—protection from unwanted telemarketing calls. We obtained the phone numbers placed on the Federal Trade Commission’s do-not-call (DNC) registry, redacted for privacy. After matching those numbers to demographic and other information based on geographic location, we regressed the observed signup frequencies on individual demographic variables to profile the DNC registrants. Grouped logits of county averages of signup frequencies were run on explanatory variables suggested by a simple choice model of the DNC registration decision and the calling pattern of telemarketers. We find that a parsimonious specification accounts for most of the variance explained by the full set of variables. Signup frequencies are larger in areas of higher incomes and greater educational attainment. They are lower for areas with greater incidence of Latino origin and linguistic isolation. The results show that a state DNC list acts as a substitute for the FTC registry unless the two are merged. Finally, we make some crude estimates of the value of the FTC’s DNC list, and also use the signup patterns, and the apparent independence from Internet access, to predict the popularity of a hypothetical do-not-spam registry.

## 1 Introduction

Technology has made it increasingly difficult to be “let alone” as the number of portals into homes and businesses continues to grow, and as access to those portals remains relatively easy. Fixed

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and mobile phones, fax machines, voice mail, email and instant messaging all represent opportunities for commercial interests to solicit consumers and invade their personal privacy in the process. This paper attempts to identify determinants of the value that individuals place on their privacy—that Constitutional right exalted by Justice Brandeis in his 1928 dissenting opinion in Olmstead v. United States.

Legal scholars have identified several facets of personal privacy.<sup>1</sup> We focus on individuals' desire for "solitude" generally, and more specifically, their desire not to be interrupted by telemarketing calls and other unwanted phone solicitations. We treat actions taken by households to protect their privacy as expressions of the value they attach to their solitude. This occurs when households subscribe to a calling feature on a phone line and use it to block or screen incoming calls. Clear evidence of demand for privacy occurs when individuals register their phone numbers on a do-not-call (DNC) program which are then removed from telemarketers' calling lists.

We exploit a natural experiment conducted by the Federal Trade Commission when it began to collect phone numbers for a national do-not-call registry last year. That program permits consumers to register landline and cellular phone numbers and penalizes all non-exempt telemarketers for calling them. The FTC list has been a big hit: more than 60 million phone numbers have been registered since it first began.

What causes people to register their phone numbers with the DNC list? We discover some answers to this question by merging the collection of registered phone numbers with household demographic information. We are especially interested in the relationship between sign-ups to the DNC list and household income, composition, race and education. We also attempt to use the pattern of DNC sign-ups to quantify:

- The monetary value that the average household attaches to blocking telemarketing calls.
- The effects of different registration modes (*e.g.*, phone vs. web) on ultimate sign-up frequencies, and whether different modes are substitutes for one another at the household level, or possibly complementary in the aggregate;
- The likelihood that consumers will register with a do-not-spam list, if and when one were to be created.

We apply standard consumer theory to describe a household's decision to protect its privacy—such as signing up with a do-not-call list or subscribing to a privacy calling feature. This leads us to a model where household's are more or less likely to sign up depending on how "annoyed" they are by telemarketing calls. While this is largely "random" we find it likely that demographic variables can have an impact. Traditionally higher income individuals put a higher value on their time and would therefore be more annoyed by telemarketers. Further a household is more likely to be annoyed the more they are called. It is clear that telemarketers use area demographics when determining whom to call.<sup>2</sup> Since some demographic factors will affect both decisions, they will

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<sup>1</sup>Two other types of privacy include "anonymity" and "secrecy." See Ruth Gavison, "Privacy and the Limits of Law," Yale Law Journal, vol. 89, 1980, pp. 421–471.

<sup>2</sup>In fact, many telemarketers use random number dialing. Since the average exchange utilization is about 50%, dialing a random number in an exchange has about a 50% chance of finding a working telephone. However, the choice of which exchanges to mine is influenced by the demographic makeup of the exchange and there are several services that supply the telemarketing industry with demographic information by telephone exchange (one of which we used for this study.)

be confounded in our empirical results. Further, due to the fact that DNC sign-ups cannot be matched with households, we must sum up these individual decisions to some aggregate regional level. While our formal analysis of consumer decision making does not generate an econometric specification directly, it guides our specification of the econometric models.

The empirical analysis begins by segmenting the phone numbers registered to the FTC list by county and then matching them to county-level demographics from the Census and other datasets. We then regress sign-up frequencies on demographic variables. Next, we estimate grouped logit models of sign-up frequencies on various combinations of demographic variables and other factors.

Many of the variables that appear significant in these specification have a natural interpretation, as do the signs on their coefficients. For instance, higher sign-ups occur in counties with higher household income and higher educational attainment. We can also interpret the strong relationships between sign-ups and the percentages of households that have a mortgage and that are “linguistically isolated.” However, some surprises arise, as when Internet penetration rates are weakly related to sign-up frequencies, if at all. The effect of age of head of household is uneven: young households have low participation in the DNC program, senior citizens have high participation, and in between the effect varies in sign and significance.

Our estimation results for DNC sign-ups are then used to make crude predictions about the popularity of a do-not-spam list, if one were created that resembled the DNC programs. Our predictions are based on the lack of correlation we found between DNC sign-up behavior and household Internet access. Finally, we offer some estimates of the aggregate monetary value to consumers of do-not-call programs.

## 2 Background

Both state and federal legislation has been enacted that enable consumers to block unsolicited telemarketing calls. The Telephone Consumer Protection Act (TCPA) of 1991 established consumers’ federal rights with respect to telemarketing calls. Last year, the Federal Communications Commission created a national registry when, in coordination with the FTC, it amended its rules implementing the TCPA.<sup>3</sup>

The national DNC program collects phone numbers that are removed from telemarketers’ calling lists. Consumers add their phone numbers either by making a toll-free phone call or by visiting the FTC’s website.<sup>4</sup> Consumers have the option to later remove a number from the registry. Only residential lines are allowed on the list but both landline and cell phone numbers can be registered.<sup>5</sup>

All telemarketers are required to “scrub” their calling lists of phone numbers on the DNC list

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<sup>3</sup>47 C.F.R. 64.1200 (June 26, 2003). The FTC’s rules were spelled out with amendments to its Telemarketing Sales Rule, 67 FR 4492 (Jan. 30, 2002).

<sup>4</sup>If the phone is used, a consumer must call from the number that is being registered, and only one number can be registered at a time. If, alternatively, the consumer signs up on the web, up to three phone numbers can be added at one time, though it requires an active email account (besides Internet access). Web-based sign-ups ran into some problems, as when the consumer did not receive the verification email reply possibly because it was screened by their spam filter, or when they could not verify registration by clicking on the provided link due to an incompatible web browser.

<sup>5</sup>Cell phones are a rare target for telemarketers because the TCPA bans the use of auto dialers to call cell phones, or leaving a prerecorded message of any kind. Then the only alternative is a hand-dialed call from a live person—an expensive option.

on a set schedule.<sup>6</sup> The national do-not-call applies to both interstate and intrastate telemarketing calls. A telemarketer who continued to call registered numbers could face fines up to \$11,000 per incident.<sup>7</sup> Exceptions were granted for three classes of callers: those protected by free speech (political campaigning, survey research), nonprofits and charities, and companies having a recent commercial relationship with the consumer.

The FTC registry is not the only, or the first, do-not-call list. When it was launched, no fewer than 27 states had maintained some arrangements for registering phone numbers of their residents. Of these, 15 states eventually decided to merge their lists with the FTC's. Consumers who registered with a state program that was merged did not also have to sign up a second time. States that declined to merge their list with the federal list often continued to run their registries in parallel.<sup>8</sup> Interestingly, whereas the FTC DNC is free to consumers, several states charge their residents to join their lists—usually a one-time fee that, while small, often requires an annual renewal fee.

Independently, the Direct Marketing Association (DMA) collects consumers' phone numbers for its "Telephone Preference Service" (TPS).<sup>9</sup> Members of the DMA are "required" to adhere to the TPS requests, but compliance with the TPS is voluntary for non-members. It is unclear how effective are the monitoring and enforcement of this program, or even what penalties are imposed for violations. According to the DMA, the TPS was "80.5 percent effective at decreasing the number of telephone solicitations."<sup>10</sup> Prior to advent of the federal DNC list, the DMA claims that approximately 7.5 million phone numbers were registered on the TPS.

Consumers can protect against unwanted calls using other means besides joining a do-not-call registry. They can subscribe to calling features offered by their local telephone companies—such as caller ID or call blocking—that enable the called party to refuse unidentified or suspicious incoming calls. Even a simple answering machine can perform some of these functions as when the consumer screens calls.<sup>11</sup> The ability to selectively choose which callers are able to reach the consumer, and which calls are accepted, give these calling features an advantage over a do-not-call list. DNC programs are rather blunt means to protect consumers as they indiscriminately excludes large blocks of telemarketing calls.<sup>12</sup>

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<sup>6</sup>Beginning on January 29, 2004, the FTC also required telemarketers to display their name and number on caller ID devices.

<sup>7</sup>FTC filed its first suit against a telemarketer for violating the DNC on August 31, 2004, United States of America v. Braglia Marketing Group, LLC, File No. 042 3036, Civil Action No.: CV-S-04-1209-DWH-PAL.

<sup>8</sup>In the reverse direction, any phone number registered directly to the FTC list must also be transferred to the corresponding state DNC list when one is active.

<sup>9</sup>Registration with TPS is free by mail and costs \$5 for 5 years for online sign-up. The sign-up page is at <http://www.dmaconsumers.org/cgi/offtelephonedave>.

<sup>10</sup><http://www.the-dma.org/cgi/dispnewsstand?article=921++++>. We cannot be certain exactly what this figure means.

<sup>11</sup>There is some evidence that many consumers believe that having their phone numbers non-listed with directory assistance or not published in the white pages will reduce their telemarketing calls. Since telemarketers rely more on purchased lists that are drawn from other sources, the benefit to these consumers is likely to be negligible.

<sup>12</sup>Consumers can selectively accept calls from a particular telemarketer under the FTC DNC program, but only by making a specific request in writing.

### 3 Model of Demand for Privacy

We apply standard consumer theory to describe a household's decision to protect its privacy—whether signing up with a do-not-call list or subscribing to a privacy calling feature. In this view, when a solicitation occurs, it likely causes some disutility for the consumer. Individuals vary in their preferences for privacy in ways that are both observable and unobservable. While not common, consumers may wish to make a transaction with the telemarketer or at least to be informed of their offering. In addition, consumers are “endowed” with different baseline levels of privacy as a consequence of their immediate environment, affecting the marginal value they attach to blocking telemarketing calls or other invasions of privacy.

Households can choose *when* to register their phone numbers if they decide to do so. We believe that consumers express greater demand for privacy when they sign up early than those who register later, though we do not explicitly model the timing decision. We do make use of the timing of registrations on occasion, however.

When deciding whether to register, a household takes into account the expected benefits that follows from having its number blocked from telemarketers, and weighs it against any cost of registering and having the number blocked. If a number is not registered, then with some probability it would be called. That probability depends on the average likelihood and frequency with which telemarketers call a particular line which, in turn, depends partly on the characteristics of the household that owns that line.<sup>13</sup>

Even if a call is placed to a line, there may not be someone present to answer. The greater the number of household members, all else equal, the greater the likelihood telemarketers will reach some person in the household.<sup>14</sup> It is before this point, however, when privacy calling features can intercept or divert an incoming call. Assuming the call reaches a live person, they can still reject the call, though it causes some nuisance by that point. And it is entirely possible that the consumer would want to do business with the telemarketer, in which case the call would offer positive benefits.

If the household registers its phone number(s) on the DNC list, the only calls that should get through would be from callers who are exempted under the rules. If an exempt call came through, it would again depend on whether someone was available to answer it, and if so, whether the solicitation was welcomed or simply an annoyance.

We can represent the household's problem by a decision tree with a series of binary branches governed by either a decision by the consumer or telemarketers, or by a chance event (see Figure 1). Associated with each final branch of the tree is a payoff to the household. We presume that a household's expected utility from alternative events will guide its decision to register with a DNC list.

As shown in the decision tree, a pre-condition for a household to join the DNC list is that it be aware of the program's existence and effectiveness. Awareness of the FTC's do-not-call registry varies over time with press coverage and competing and complementary events (*e.g.*, each

<sup>13</sup>In fact, many telemarketers use random number dialing. Since the average exchange utilization is about 50%, dialing a random number in an exchange has about a 50% chance of finding a working telephone. However, the choice of which exchanges to mine is influenced by the demographic makeup of the exchange and there are several services that supply the telemarketing industry with demographic information by telephone exchange (one of which we used for this study.)

<sup>14</sup> It is possible that having a larger household with more people answering the phone also reduces the annoyance by distributing it over multiple people, specifically shielding the household decision makers.

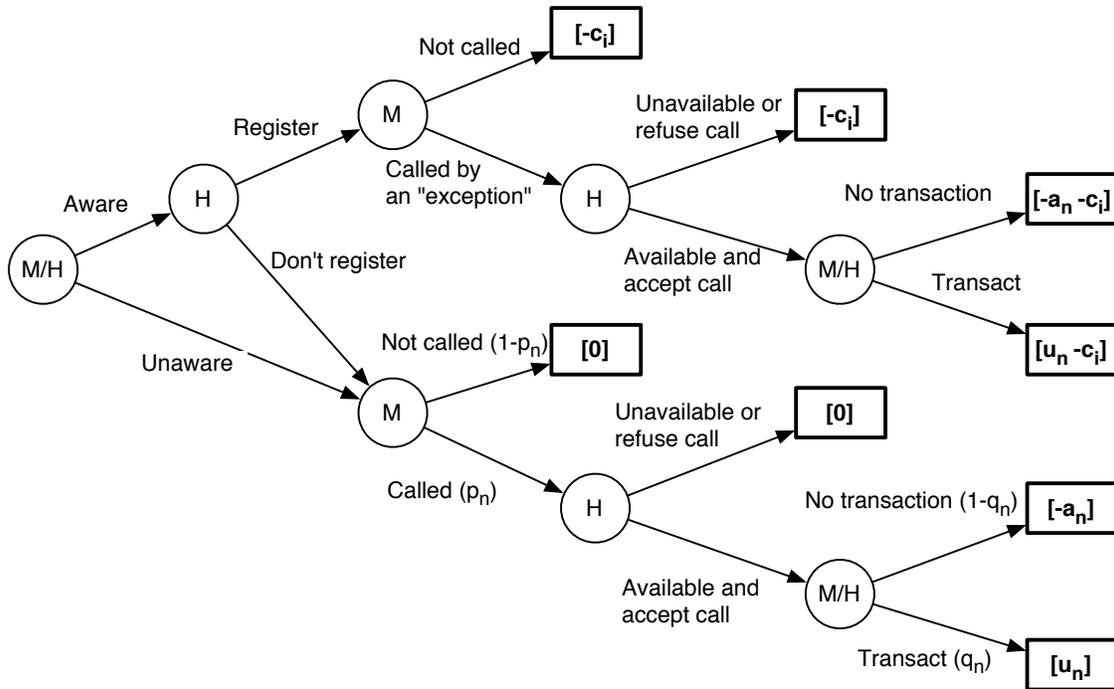


Figure 1: Household decision tree for DNC sign-ups

legal challenge to the registry and each report of a lawsuit against a telemarketer). We also expect variation in awareness across region if only because state programs might raise residents' familiarity with the concept of a do-not-call registry, possibly spread through word of mouth.

Each element of the tree contributes to a household's expected utility, and hence, explains the signup frequencies we observe. To illustrate, consider some factors that bear on a few of these elements. The more difficult and costly it is to signup for a DNC list, the less likely we would expect an average household to do so. Some state DNC programs charge residents for placing their phone numbers on their lists, raising the value of the signup cost  $c_n$ . See Table in Appendix A for a listing of state programs with their registration fees. Many, but not all, state lists allow households to register by the Internet, and for those households with Internet access at home or work, the cost of signing up, on average, will be lower than for those without access.

Telemarketers are also part of this equation especially with regard to the likelihood and the frequency with which they call a phone number. This calling pattern is captured here by  $p_n$ . At least in part, these probabilities reflect the telemarketing community's assessment of the desirability of certain households, which means the likelihood they will complete a profitable transaction. Telemarketers also have some control over the extent of the annoyance they cause when their solicitation is unwanted,  $a_n$ .

### 3.1 Random Utility Model of Do-Not-Call Registration

We adopt a random utility approach to model decisions to register with a do-not-call list. Individual choices can then, in principle, be summed to the same level of aggregation as the available

demographic data.

The first issue that must be addressed is to identify the relevant decision maker. One candidate is the household since its members may make a single decision whether to register its various lines, each of which contribute to the invasion of members' collective privacy. Alternatively, adult persons could make registration decisions on a line by line basis. This might make sense for cellular phone lines that are rarely shared by multiple individuals. Since we will eventually exclude cell lines from the empirical analysis for various reasons, we feel justified in taking the household as the decision maker.

Taking a simplified view of the household decision problem in the previous section, if household  $n$  registers its line(s) with the do-not-call list, the realized utility will be:

$$u_{1n} = v_n(y_n - c_i, z_n) + \epsilon_{1n} \quad (1)$$

where  $v_n(y_n, z_n)$  is deterministic utility associated with household income  $y_n$  and demographic characteristics  $z_n$  (*e.g.*, race, education) and where  $c_i$  represents the monetary equivalent of out-of-pocket and intangible costs of signup in region  $i$ . Note that we have not allowed for the possibility of some exempted and prohibited calls.

When the household does *not* register, it believes that it will be called with probability  $p_n$ , in which case its expected utility will be:

$$\begin{aligned} u_{0n} &= p_n [v_n(y_n, z_n) - a_n] + (1 - p_n)v_n(y_n, z_n) + \epsilon_{0n} \\ &= v_n(y_n, z_n) - p_n a_n + \epsilon_{0n} \end{aligned} \quad (2)$$

As before  $a_n$  is the disutility of a telemarketing call specific to household  $n$ . Household  $n$  will register when  $u_{1n} > u_{0n}$ , or equivalently, when

$$\begin{aligned} v_n(y_n - c_i, z_n) + \epsilon_{1n} &> v_n(y_n, z_n) - p_n a_n + \epsilon_{0n} \\ \epsilon_{1n} - \epsilon_{0n} &> [v_n(y_n, z_n) - v_n(y_n - c_i, z_n)] - p_n a_n \end{aligned} \quad (3)$$

Let  $F(\bullet)$  be the c.d.f. of the difference between the two disturbances. Then the likelihood of registration is:

$$\phi_n = 1 - F[v_n(y_n, z_n) - v_n(y_n - c_i, z_n) - p_n a_n]$$

If we were to assume that the deterministic part of household utility is linear in the variables, *i.e.*,  $v_n(y_n, z_n) = \beta_0 + \beta_y y_n + \beta_z z_n$ , then the term in the distribution function simplifies to just  $\beta_y c_i - p_n a_n$  where  $\beta_y$  is the marginal utility of income. Simple comparative static exercises confirm that, as expected, signup frequency is decreasing in cost of signing up and increasing in the magnitude of the annoyance:  $\frac{\partial \phi_n}{\partial c_i} = -f\beta_y < 0$  and  $\frac{\partial \phi_n}{\partial a_n} = fp_n > 0$ .

### 3.2 Telemarketers' Calling Behavior

Telemarketers are presumed to follow systematic rules for calling potential customers even if that involves some randomization. We assume these rules are optimal—just as in the case of households' decisions to register with a DNC list. In its simplest form, if the telemarketer makes a call to household  $n$ , it will either succeed or fail to generate a transaction. Let the chance of success be  $q_n$

for household  $n$  given the call goes through. This conditional probability depends on characteristics of the household among other factors. Telemarketers would prefer to only call those lines that resulted in profitable transactions, but they must rely on noisy signals.<sup>15</sup> If the telemarketer meets with success, it realizes a profit of  $t_n$ .

Consider the problem facing a representative telemarketer. Expected profitability of calling household  $n$  is dependent on the likelihood of a successful transaction and the profitability of a transaction if one occurs:

$$\begin{aligned}\pi_n &= q_n(t_n - c) + (1 - q_n)(-c) + \nu_n \\ &= q_n t_n - c + \nu_n\end{aligned}\tag{4}$$

The error term,  $\nu_n$ , captures the cost to the telemarketer of calling the household, plus any randomness in the household's willingness to transact or any randomness in selection of a target (*e.g.*, random number dialing). The cost of making a call  $c$  is assumed not to vary across households and is independent of whether the call is successful or not.

Conditional on the error term, the telemarketer (or its software program) decides to call household  $n$  when  $\pi_n > 0$ . From the perspective of household  $n$  (and the researcher), however, a telemarketing call is a binary random variable with probability:  $p_n = \Pr\{\pi_n > 0\}$ . Assuming households have rational expectations, this probability will enter random utility (2).

While consumer characteristics like income and demographics do not appear explicitly in the expression for telemarketer's call profitability, those variables enter indirectly through their influence on the likelihood of a transaction,  $q_n$ , and the profitability of a transaction,  $t_n$ . Looking ahead to empirical estimation, we should not presume an unambiguous relationship between DNC signup frequencies and demographic variables. Take household income. Higher income may raise the value of time, and thus the annoyance from unwanted telemarketing calls. It also may raise the expected profitability should a transaction occur. These two tendencies reinforce one another, increasing the value of registering with the DNC list. However, the likelihood of a transaction with higher income consumers could be lower than those with lower income, making a call to these lines less attractive to telemarketers, reversing the effect of income. We only observe the net effect of income (and other demographic variables) on DNC signup frequencies and are not yet able to instrument for these intervening factors.<sup>16</sup>

<sup>15</sup>Indeed, some telemarketers recognize the benefits in do-not-call programs as they weed out households who are annoyed by calls and would not make a purchase anyway. See Robert Gutsche Jr., "Telemarketing firms face their toughest call: Costs of new rules push many companies to brink," *Chicago Tribune*, February 25, 2004.

<sup>16</sup>Express the probability that a telemarketer will call household  $n$  as follows:

$$p_n = \Pr\{\pi_n > 0\} = \Pr\{\nu_n > c - q_n t_n\} = 1 - G(c - q_n t_n),$$

where  $G(\bullet)$  is the conditional c.d.f. of the profitability disturbance. Then substitute into the household choice probability to get:

$$\phi_n = 1 - F\{\beta_y c_i - [1 - G(c - q_n t_n)] a_n\}$$

Differentiating with respect to income  $y_n$  we get that:

$$\partial\phi_n/\partial y_n = -f \times \left[ -g \left( \frac{\partial q_n}{\partial y_n} t_n + q_n \frac{\partial t_n}{\partial y_n} \right) a_n - (1 - G) \frac{\partial a_n}{\partial y_n} \right]$$

which cannot be signed without further assumptions on the signs of the various income effects.

### 3.3 Geographic Aggregation of Signup Frequencies and Household Demographics

We cannot associate any registered phone number with a household, and consequently, we cannot estimate a household choice model explicitly. We can, however, associate fixed-line phone numbers with a geographic region. This is done using the relationship between a fixed line and the local exchange company’s “wire center” and the geographic location of the wire center.

As before, let  $n$  index households and define  $N_i$  as the set of households that are located in region  $i$ . Assume that a household registers all of its (fixed) lines if it chooses to register any one of them. In that case, we can form the frequency of DNC signup in region  $i$  as:

$$f_i = \frac{\sum_{n \in N_i} l_n \phi_n}{\sum_{n \in N_i} l_n} \quad (5)$$

where  $l_n$  is the number of lines owned by household  $n$ . Averaging the explanatory variables takes a slightly different form; in the case of average household income in region  $i$ :<sup>17</sup>

$$\bar{y}_i = \frac{\sum_{n \in N_i} y_n}{\#N_i} \quad (6)$$

We choose to aggregate up all variables to the county level (specifically, the 5-digit FIPS code), reducing over 60 million phone numbers to about 3,100 observations.

## 4 Data

We obtained redacted information on the nearly 60 million phone numbers that were entered into the FTC’s do-not-call registry from June 27, 2003 through November 1, 2003 (along with the time and date each number was registered).<sup>18</sup> To ensure privacy, only the area code and exchange prefix of the number (the so-called “NPA-NXX,” or more simply, “the exchange”) was reported in the dataset.<sup>19</sup> The signups by exchange were then mapped to counties using a database purchased from the Melissa Data Corporation—one that is often used by telemarketers themselves.

Figure 2 plots the time series of frequency of phone numbers added to the FTC registry in each of the 128 days for which we have data. The large portion of sign-ups in the first few days of the program suggests a pent up demand for the do-not-call list. A spike occurs starting July 7, the first day that states east of the Mississippi could register using the toll-free number. Another spike can be found right before September 1, 2003. This one corresponds with the fact that sign-ups made prior to that day would be included when the list first went into effect on October 1, 2003 rather than waiting 90 more days before numbers are blocked. Several other smaller spikes occurring throughout the sample period come disproportionately from specific states. We use this correlation, along with independent information, to attribute each of 15 dates to the merger of

<sup>17</sup>In fact, the Census data is collected in “bins” although they report median incomes as well as frequencies by bin.

<sup>18</sup>The FTC supplied these data in response to a standard Freedom of Information Act request.

<sup>19</sup>No personal identifying information was collected along with the registered phone numbers. To further ensure confidentiality, we dropped from the analysis exchanges with 10 or fewer observations.

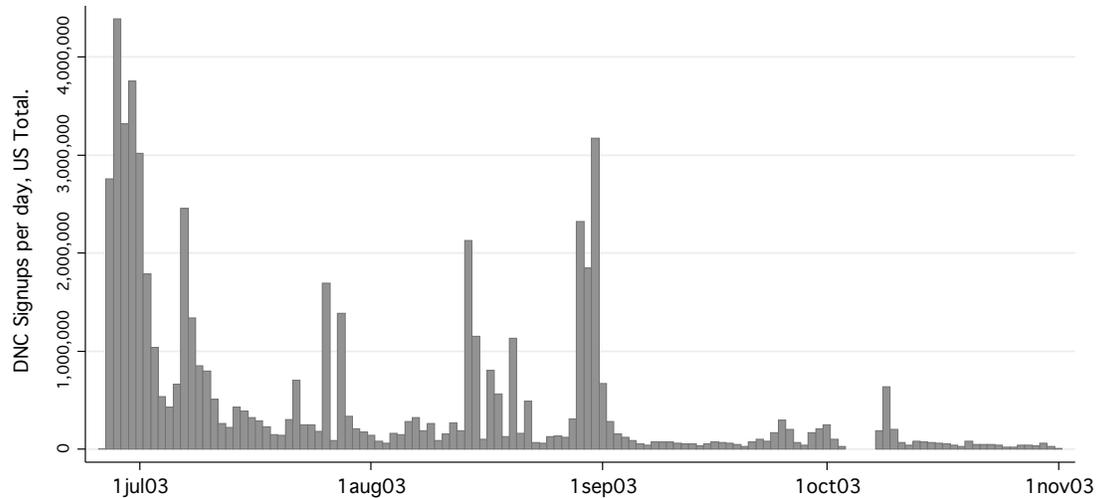


Figure 2: DNC sign-ups over time

a state list with the national list. More information on the individual statelists is available in Appendix A.

The DNC data are recorded *by phone number* but decisions to register are made *by individuals* and *by households*. Since both individuals and households often have more than one phone number (multiple fixed lines plus cellular phones), we examine both the number of households per county as well as an estimate of the number of fixed lines per county as the denominator to form sign-up frequencies.

Most of our demographic variables are extracted from the 2000 Census, including household income, size, race and composition as well as home value and mortgage. These data are supplemented with survey information from household-level panels run by the Census Bureau's Current Population Survey and TNS Telecom's ReQuest Market Monitor<sup>®</sup>Survey dataset. Those panels are also rolled up to the county level to generate the average Internet usage and lines per household. We provide greater detail about the primary data sources and construction of variables in Appendix B.

## 5 Descriptive Statistics

We begin by looking at the responses to the do-not-call list on a state by state basis. Figure 3 shows the proportion of households that has signed up for the FTC DNC list. The total sign-ups have been adjusted to exclude numbers on non-wired exchanges and to adjust for the average number of lines per household in each state. State specific do-not-call lists are identified in the figure as well as states that chose not to merge their lists.

Five of the 27 states with their own DNC initiative simply used the Direct Marketing Association's TPS list which has a charge if a consumer registers on line. Additionally, six other state programs charged for their service. We find that charging for a do-not-call list depresses the frequency of sign-up. Of all the signups on the national list that occurred in our sample period, we attribute 11.8% to the merger of state lists. Looking just at free state programs, 14.3% of the

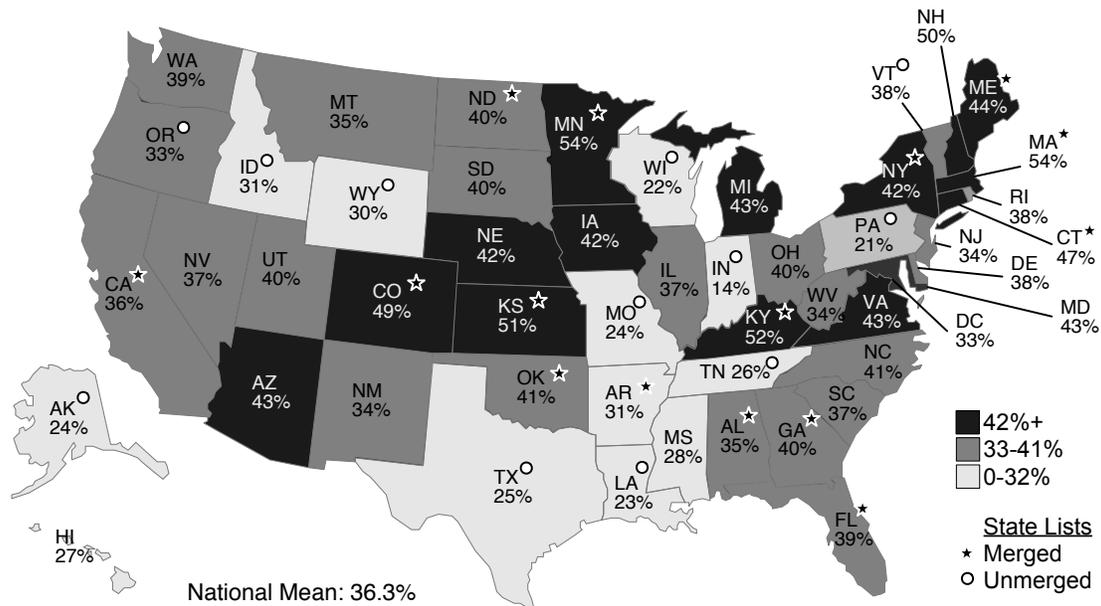


Figure 3: DNC registrations per household as of November 1, 2003.

signups came from state lists. Compare that with 7.2% for states that used the DMA’s TSP, and also the mere 1.0% for those states that charged for signups.

Turning to our demographic variables and other explanatory factors, we include Table 1 contains the key explanatory variables that are used in the econometric analysis. For the complete set of summary statistics see Table 28 in Appendix C. The definitions of a selected few census variables are included in Appendix ??.

## 6 Demographics and Sign-up Frequencies

Our first goal is to describe the relationships between demographic categories and the observed frequencies of DNC sign-up. In this section we perform regression analysis of these relationships, examining one demographic variable at a time.

Using Census data, we determine the fraction of the households (or population) in each county that falls into a given demographic category. For example, in a particular county it may be that 96.3 percent of the households are White, 2.3 percent are Black, 0.006 percent are Asian, and so on. There is typically an “Other” category, so that the fractions generally sum to 1.

Suppose that in a given county  $i$ ,  $s_i$  households sign up for the DNC list and that there are  $h_i$  households in total and  $n_{ig}$  of those are classified in demographic group  $g = 1, \dots, G$ . We suppose that the demographic classification is complete so that  $\sum_{g=1}^G n_{ig} = h_i$ .

Table 1: Summary statistics for key variables, county averages

Variable Name	Definition	Mean	Std. Dev.	Min.	Max.
pop	No. people	90,612	294,412	444	9,519,338
hh	No. households	33,978	104,956	185	3,136,279
Phone	No. fixed lines	33,130	102,818	178	3,079,273
dncland	Fixed line signups	15,390	49,257	16	1,311,045
pDNC	Signups per household	0.39	0.19	0.00	2.09
HHRaceWhite	White heads of households	0.87	0.15	0.07	1.02
HHLatino	Latino heads of households	0.04	0.10	0.00	0.97
HHInc_Med	Median HH income	35,327	8,827	15,805	82,929
EduLow	Heads of household with highschool education or less	0.13	0.05	0.02	0.33
HHLingIso	Linguistically isolated	0.02	0.03	0.00	0.34
OwnHome	Own home	0.74	0.08	0.20	0.90
HasMortgage	Mortgage on home	0.57	0.13	0.12	0.93
HHPoverty	Below poverty line	0.14	0.06	0.02	0.48
UnmarriedPartners	Unmarried partners	0.04	0.02	0.00	0.15
NoMale	No male present	0.26	0.05	0.12	0.48
pInternet	Home with Internet access	0.48	0.13	0.04	0.87
N			3094		

Proportions of households reported if not stated otherwise.

Let us assume that a *constant* fraction  $\alpha_g$  of demographic group  $g$  signs up for the DNC list in every county. Then we can write

$$s_i = \alpha_1 n_{i1} + \dots + \alpha_G n_{iG}.$$

or

$$f_i = \frac{s_i}{h_i} = \alpha_1 \frac{n_{i1}}{h_i} + \dots + \alpha_G \frac{n_{iG}}{h_i},$$

The fraction on the left is the frequency of DNC registration in a given county. The variables on the right are the fractions reported in the Census for each demographic group. Under the assumption of common sign-up frequencies of demographic groups across counties, we can estimate this relationship as a simple linear regression.

We interpret the coefficients  $\alpha_g$  as the average fraction of the particular demographic group that

signs up for DNC. Under this interpretation,  $\alpha_g$  should always be between 0 and 1. In practice, the estimated coefficients do not always satisfy this requirement, since the model is not literally true: the fraction of sign-ups of a given group is not a constant, so there will typically be nonlinearities and cross-variable effects.

Nevertheless, it may be approximately true, and this way of summarizing the data appears to be useful and give intuitively plausible results about the marginal impact of demographic variables on frequency of sign-up. In cases where  $\alpha_i$  is greater than 1 or less than zero, we will simply indicate that the corresponding effect is “large” or “small.”<sup>20</sup>

The coefficients in these regressions should *not* be interpreted as the incremental effect of one variable, holding everything else constant. Rather they should be interpreted in the sense of a marginal frequency distribution—how would we expect the frequency of sign-up to change when we move from a county with one distributions of races to another county with a different distribution of races, where other variables (income, housing, age, etc.) also change. These regressions are purely description in nature and should not be given a causal interpretation.

There is one final complication. In some cases the Census data reports the fraction of households; in other cases the Census data reports fraction of the population. Since we have the raw DNC sign-ups, we can divide by either number of households or the population, depending which normalization the Census report uses. The interpretation of the regressions coefficients will be different, depending on which normalization is used. In most cases the coefficient will represent fraction of households; in one (highest level of education attained by population 25 and older) it will represent a fraction of the population.

For example, Table 2 depicts the effect of race on the frequency of sign-up, where we have normalized by households. Roughly speaking, it appears that about 40% of Whites signed up, 15% of Blacks and low percentages of Native Americans, Pacific Islanders, and Others. However, a substantial percentage of Asians and Multirace households signed up. The column in the table labeled “Mean” indicates the fraction of the population represented by each demographic group. Table 3 shows the same regression with population used as the normalizing variable. The results are essentially consistent, reflecting the relative constancy of population per household: the mean is about 2.54, and half of the data lies between 2.48 and 2.71. So, for example, 2.6 times the coefficient on pRace.White in the population regression is 0.383, not terribly far from the 0.396 in the household regression. The sign pattern and relative magnitudes of the coefficients are about the same, so to keep things consistent, we will report the data for the household normalization only in what follows.<sup>21</sup>

“Latino” is a separate classification from race and refers to country of origin. According to Table 4 they have a somewhat lower frequency of sign-up compared to non-Latinos. Figures 4 and 5 depict a simple scatterplot of the relationship between the frequency of sign-up for DNC and the fraction of the population that falls into the indicated groups. As can be seen, there is considerable variation across counties, but those with a high proportion of Blacks or Latinos definitely have a lower frequency of sign-up.

<sup>20</sup>We also estimated the regressions constraining  $\alpha_i$  to lie between 0 and 1 and found that the results were essentially what one would get by just truncating the coefficient. That is, there was generally no impact on the other coefficients from forcing coefficients to lie in the 0-1 interval. For this reason we report the unconstrained regressions.

<sup>21</sup>Please note that the tables should test if the estimates are different from the population mean, 0.382 rather than 0. That will be addressed in a future version of th paper.

Table 2: Race regression—Households

Variable	Coeff.	Std. Err.	Mean
pHHRace_White	0.396**	0.004	0.870
pHHRace_Black	0.155**	0.019	0.077
pHHRace_Native	-0.066	0.046	0.016
pHHRace_Asian	2.688**	0.218	0.006
pHHRace_PacIs	-14.072**	1.422	0.000
pHHRace_Other	-0.499**	0.079	0.018
pHHRace_Mult	2.125**	0.353	0.011

Table 3: Race regression—Population

Variable	Coeff.	Std. Err.	Mean
pRace_White	0.151**	0.002	0.845
pRace_Black	0.053**	0.007	0.087
pRace_Native	-0.055**	0.016	0.018
pRace_Asian	0.649**	0.068	0.008
pRace_PacIs	-4.456**	0.431	0.001
pRace_Oth	-0.215**	0.025	0.025
pRace_Mult	1.182**	0.116	0.015

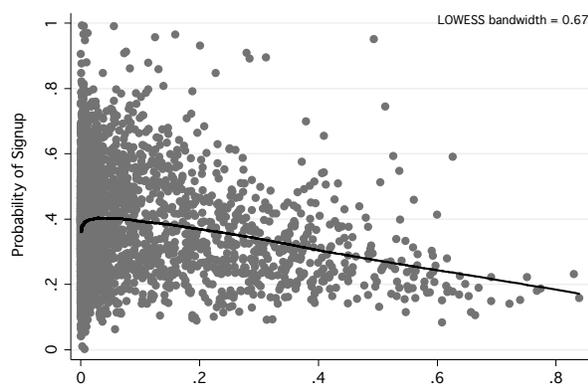


Figure 4: Frequency of sign-up vs. fraction of population that is Black.

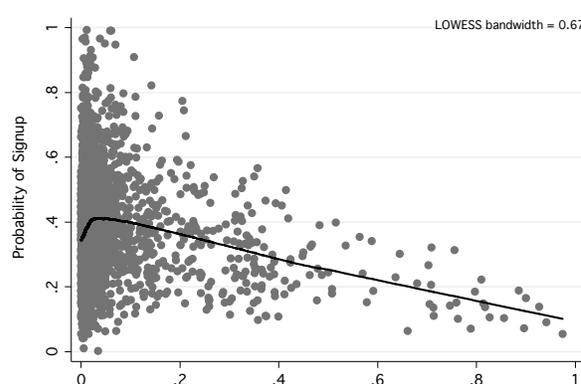


Figure 5: Frequency of sign-up vs. fraction of population that is Latino.

Age (of the householder), depicted in Table 7 does not seem to have any consistent impact on the likelihood of signing up. It is worth noting that only 5 percent fall in the 15–24 category but the standard error is still low (and the estimate positive). Table 6 looks at the frequency of sign-up as a function of household size, with 2 and 4-person households having a high probability of signing up. Curiously households with 5 or more people seem to have a lower frequency of signing up. Perhaps larger households have a lower baseline level of privacy, so the incremental addition to overall privacy from DNC is low. Alternatively it may be the case that the annoyance of telemarketer’s calls is spread over a larger number of people. Households with young children are more likely to sign-up while households with older children are less likely to do so (table 5). The first effect could be attributed to the fact that someone will be at home with the very young children, making the probability that someone is home when a telemarketer calls higher.

The effect of income on sign-up is shown in Table 8. As one might expect, low income households have a low probability of sign-up. The frequency of sign-up generally rises with income, though the estimated coefficients are typically insignificant. However, households with incomes over \$100,000 have a substantial likelihood of signing up.

The impact of education is summarized in Table 9. Those with education of grade school or less have a low frequency of signing up, and high-school dropouts even more so. Those with a

Table 4: Latino Households

Variable	Coeff.	Std. Err.	Mean
Latino	0.169**	0.026	0.045
Not Latino	0.392**	0.003	0.955
Diff.	-0.223**	$F(1, 3092) = 66.28$	

Table 5: Presence of Kids by Age

Variable	Coeff.	Std. Err.	Mean
Below 5	1.122**	0.204	0.147
5-11	0.126	0.175	0.244
12-18	0.765**	0.119	0.220

Table 6: Household Size (# members)

Variable	Coeff.	Std. Err.	Mean
1	0.386**	0.072	0.253
2	0.753**	0.065	0.347
3	-1.454**	0.157	0.162
4	2.463**	0.210	0.138
5 up	-0.823**	0.096	0.100

Table 7: Age of Householder

Variable	Coeff.	Std. Err.	Mean
15-24	0.559**	0.127	0.048
25-34	0.080	0.135	0.145
35-44	0.554**	0.142	0.213
45-54	1.146**	0.153	0.198
55-64	-0.444*	0.198	0.147
65-74	-0.232	0.198	0.128
75 and up	0.780**	0.114	0.121

post-graduate education are quite likely to sign-up.<sup>22</sup>

Table 8: Household Annual Income ('000 dollars)

Variable	Coeff.	Std. Err.	Mean
Below 10	-0.472**	0.093	0.121
10-15	0.369	0.242	0.081
15-20	0.732**	0.249	0.078
20-25	0.230	0.260	0.079
25-30	0.283	0.275	0.075
30-35	0.379	0.276	0.072
35-40	1.060**	0.299	0.065
40-45	-0.023	0.325	0.060
45-50	0.491	0.350	0.052
50-60	0.891**	0.251	0.088
60-75	0.219	0.235	0.090
75-100	-0.085	0.235	0.074
100 and up	1.528**	0.109	0.066

Table 9: Education by Householder

Variable	Coeff.	Std. Err.	Mean
Grade School	0.087	0.057	0.091
Some High Sch.	-0.191**	0.067	0.135
High School	0.239**	0.031	0.348
Some College	0.720**	0.046	0.262
College Grad.	0.414**	0.105	0.109
Post Grad.	1.506**	0.134	0.055

Table 10 indicates that those households with mortgages have a higher frequency of signing up, while Table 11 shows that sign-up frequencies tend to be low in areas where poverty rates are high. We found in Table 12 that counties with a high fraction of Internet users tended to have higher sign-ups rates, but not by a dramatic amount.

<sup>22</sup>In later models we merge the first two categories into a new "low education" variable.

Table 10: Household has Mortgage

Variable	Coeff.	Std. Err.	Mean
Yes	0.576**	0.009	0.573
No	0.121**	0.012	0.427
Diff.	0.455**	$F(1, 3092) = 483.83$	

Table 11: Household Living in Poverty

Variable	Coeff.	Std. Err.	Mean
Yes	-0.513**	0.036	0.142
No	0.530**	0.007	0.858
Diff.	-1.043**	$F(1, 3092) = 612.80$	

Table 12: Internet Access at Home

Variable	Coeff.	Std. Err.	Mean
Has Internet	0.431**	0.012	0.486
No Internet	0.335**	0.011	0.514
Diff.	0.096**	$F(1, 3092) = 18.94$	

Table 13: Male Adult Present

Variable	Coeff.	Std. Err.	Mean
No	0.216**	0.043	0.261
Yes	0.441**	0.0157	0.739
Diff.	-0.225**	$F(1, 3092) = 15.07$	

With respect to marital status, Tables 14 and 13 indicate that counties with a high fraction of unmarried partners have a much higher frequency of DNC registration than counties without, and that the presence of a male is correlated with an increased sign-up rate. “Linguistic isolation,” a census category referring to lack of English fluency measured at the household level, dramatically reduces the frequency of sign-up, as shown in Table 15. It is worth pointing out that this is a very small group in any county.

Table 14: Household of Unmarried Partners

Variable	Coeff.	Std. Err.	Mean
Yes	1.146**	0.186	0.043
No	0.348**	0.009	0.957
Diff.	0.798**	$F(1, 3092) = 16.86$	

Table 15: Household Linguistically Isolated

Variable	Coeff.	Std. Err.	Mean
Yes	-0.206*	0.093	0.017
No	0.392**	0.003	0.983
Diff.	-0.186**	$F(1, 3092) = 39.79$	

When looking at the relative urbanization of the counties we find that a higher degree of urbanization increases the likelihood of signing up for the DNC. Perhaps these areas have a greater awareness of the DNC registry due to greater mass media and word-of-mouth exposure. Nevertheless, Table 16 reveals that farming communities tend to have a higher sign-up rates than any other category.

Table 16: Urban/Rural Area

Variable	Coeff.	Std. Err.	Mean
Urban	0.466**	0.006	0.396
Urban Area	0.492**	0.008	0.164
Urban Cluster	0.427**	0.010	0.232
Rural	0.327**	0.005	0.604
Farm	0.611**	0.070	0.040
Non-Farm	0.315**	0.007	0.564

## 7 A Grouped Logit Model of Sign-up Frequencies

Following the logic of the choice model described earlier, we specify a logistic regression model of the form:

$$\log\left(\frac{f_i}{1-f_i}\right) = \beta_0 + \beta_1 x_{1,i} + \dots + \beta_k x_{k,i} + \epsilon_i$$

where  $f_i$  is the sign-up frequency in county  $i$  and the  $x$ s are explanatory variables. These frequencies are formed according to (5) and the explanatory variables are county averages calculated according to (6).

The regression coefficients cannot easily be interpreted as structural demand parameters due to confounding with telemarketer behavior. Rather, this should be viewed as a nested specification. The models are estimated using weighted least squares with the weights proportional to  $1/\sigma_j^2$  where

$$\sigma_i^2 = \frac{1}{n_i f_i (1 - f_i)}$$

and  $n_i$  is the number of households in county  $i$ . Table ?? provides the regression results for a number of different model specifications. We report odds ratios ( $e^b$ ) rather than  $b$ . Standard errors and t-tests are similarly transformed.<sup>23</sup>

The probability of signing up for the FTC DNC list is larger in counties comprised of households with higher incomes. Not surprisingly, low education (*i.e.* never finished high-school) and household linguistic isolation have negative impacts on registration. It is harder to explain the consistent positive impact by a high proportion of Latino households in the county and the negative impact of teenagers. Unexpectedly, once we control for these other variables, Internet penetration does not make much of a difference on DNC sign-ups.

Perhaps the most interesting result is how much explanatory power can be derived from only three variables: Income, Teenagers and Low Education. Compared to Models 7 and 8 that only use state level variables, these three variables raise the adjusted  $R^2$  by 27% and 25% for the models without and with state dummies, respectively. Even throwing in the full kitchen sink contributes only an additional 5–6%.

The Census reports household income in bins as well as a median. For these models we have

<sup>23</sup>Odds ratios measure the impact of the variable on the relative odds of signing up for the DNC list. No effect is measured by an odds ratio of 1.

Table 17: Full model grouped logit results, odds ratios

	Kitchen Sink		Parsimonius I		Parsimonius II	
	(1)	(2)	(3)	(4)	(5)	(6)
log[Median Inc]	4.561**	2.634**	2.746**	2.772**	2.017**	2.028**
p[Latino]	1.887**	2.017**	3.976**	2.759**		
p[Kids 12–18]	0.017**	0.050**	0.082**	0.084**	0.224**	0.258**
p[Ling.Iso.]	0.034**	0.045**	0.007**	0.011**		
p[Low Edu.]	0.110**	0.079**	0.034**	0.035**	0.004**	0.002**
Has List	0.482**	0.773	0.499**	0.804	0.507**	0.674*
Merged List	2.568**	1.564*	2.459**	1.580*	2.344**	1.572*
Ksink Controls	Yes	Yes				
State Dummies		Yes		Yes		Yes
Adjusted $R^2$	0.61	0.75	0.58	0.72	0.55	0.70
Observations			3094			

Significance levels: † : 10% \* : 5% \*\* : 1%

chosen to use the median since this allows us to construct an imperfect measure of income elasticity from the grouped logit results. Our estimates are evaluated at median national household income and given in Table 18 for each of the six grouped logit specifications. All estimates are positive with very small standard errors, and indicate rather income inelastic demand for DNC protection.<sup>24</sup>

Table 18: Income Elasticities for grouped logit models

Model	Elasticity	Std. Err.	$P >  z $
(1) Kitchen Sink	0.939	0.090	0.000
(2) Kitchen Sink, SD	0.604	0.089	0.000
(3) Parsimonius I	0.626	0.029	0.000
(4) Parsimonius I, SD	0.632	0.032	0.000
(5) Parsimonius II	0.437	0.026	0.000
(6) Parsimonius II, SD	0.441	0.028	0.000

Elasticities Calculated at the Median Income: \$35,348

## 8 Demand for a Do-Not-Spam List

Considerable pressure has been brought to bear on the federal government to “do something” about spam email. Government regulators have been resisting any action, many of whom feel that

<sup>24</sup>The calculated elasticities are for the probability of sign-up over median income,  $\frac{\partial \log(\text{pdncland})}{\partial \log(\text{Inc}_{\text{Med}})}$ .

enforcement of a do-not-spam law is futile. Nevertheless, it is worth while to speculate about how many sign-ups a do-not-spam list might elicit based on our results for do-not-call.

We begin by making the bold assumption that the propensity to sign up for a do-not-call list is a good approximation for the propensity to sign up for a do-not-spam (DNS) list. Of course, only that subset of the population having Internet access—or more specifically, using email—are candidates for a DNS list. To estimate the proportion of this population that would register, we simply multiply by the observed (marginal) frequency of DNC registrations. This calculation is accurate provided sign-up for the DNC list and subscription to Internet access are roughly independent variates for U.S. households. In fact, we find these two variables to be nearly orthogonal, approaching this relationship from two distinct directions.

The Pew Foundation has sponsored a series of telephone surveys regarding Internet use.<sup>25</sup> A June 2003 Pew telephone survey asked 2,200 Americans several questions about their attitudes towards spam and telemarketing. Table 19 indicates how annoying spam and telemarketing were perceived to be. (In these tables “DK” is “don’t know” and “NA” is “not applicable.”)

Table 19: How much annoyance comes from ...

Type	DK	NA	None	Small	Big	Very big
Telemarketing	25	40	152	275	755	953
Email spam	2	847	86	205	509	661

Surprisingly, roughly 20 percent of respondents indicated that telemarketing and spam caused “no” or “small” annoyance. (On the other hand, spam has gotten increasingly more prevalent in the time since the June 2003 Pew survey.) Looking at the cross tabulation in Table 20, it is clear to the naked eye that the same people who were not bothered by either spam or telemarketing. A Chi-squared test rejects non-independence at a very high level of significance.

Table 20: Spam and telemarketing responses

Spam	Telemarketing					
	DK	NA	None	Small	Big	Very big
DK	1	0	0	0	1	0
DNA	22	28	87	98	259	353
None	0	1	23	13	17	32
Small	0	0	7	64	69	65
Big	1	6	12	64	257	169
Very	1	5	23	36	152	334

This suggests that pretty much the same fraction of households who signed up for the do-not-

<sup>25</sup>Survey results along with the raw data are available at <http://www.pewinternet.org/datasets/index.asp>.

call list would sign up for a do-not-spam list given that they are Internet users. This conclusion is confirmed by both our simple demographic model reported in Table 12 and the results reported in Table 17. Columns (1) and (2) in those two tables indicate that Internet usage and DNC registrations nearly orthogonal. A simple correlation calculation between pInternet (the probability of having and using Internet access at home) and pdncland (the probability of a household signing up for the DNC list) is a mere 0.078.<sup>26</sup>

To further examine the relationship between Internet usage and DNC registration we take advantage of an (unintentional) design feature of the FTC’s implementation. As described above, only Internet sign-up was possible for users east of the Mississippi during the first 10 days of the program, whereas those west of the Mississippi could sign-up using a toll-free phone number as well. We extend model 4 from Table 17 with a geographical dummy to divide the country at the Mississippi and run the regression interacting the east/west dummy with Internet usage.<sup>27</sup>

Table 21: DNC grouped logit regression on signups before and after July 7 and separated by states east and west of the Mississippi. Odds ratios.

	Jun 27–Jul 6			Jul 7–Nov 1
	(1)	(2)	(3)	(4)
pInternet	1.026 (0.064)	1.026 (0.064)	0.656** (0.054)	0.617** (0.062)
east		1.121 (0.127)	0.770* (0.094)	1.474* (0.266)
east×pInternet			2.069** (0.185)	1.215† (0.132)
Controls	yes	yes	yes	yes
Observations	3094	3094	3094	3094
Adjusted $R^2$	0.79	0.79	0.79	0.80

Significance levels : † : 10% \* : 5% \*\* : 1%

Other controls: IHHInc.Med, pHHLatino, pKids12t18, pHHLingIso, pEduLow, HasList, MergeList and state dummies

Columns (1)–(3) report the results of the grouped logit model on sign-ups during the period June 27, 2003 through July 6, 2003. It is important to note that the base effect of the Internet is negative (just as in the main model) but that it is significant and positive for counties east of the Mississippi. The latter is no surprise since the Internet was the only way to sign up during that period, the restriction limited the sign-ups or at least forcing the mode of sign-up. Column (4) contains the equivalent grouped logit for the subsequent period July 7–November 1, 2003. The estimate for sign-ups in the east, *east*, is significantly larger in (4) than in (3), thus not having access to a toll-free number the first week caused a catch up effect in the next period.

<sup>26</sup>Significant at the 0.01% level.

<sup>27</sup>Our predicted Internet usage is not significantly different between the two halves of the country: 51.6% in the west and 47.2% in the east, not statistically significant.

Although there may be a statistically significant and positive relationship between the sign-up for the FTC DNC list and household Internet usage, we believe it is economically defensible to assume orthogonality given the results reported in this section. Thus, a rough forecast of the number of sign-ups for a do-not-spam list would be the number of those who signed up for do-not-call, adjusted for the fraction of the population that has Internet access.

This is easily computed from the data we have available. At the aggregate level, about 47 million households signed up for DNC (45 percent of the total), and about 54 percent of the households in our sample had Internet access (as of the 2000 Census.) So our (very rough) forecast would be that about 25% of U.S. households would sign up for a do-not-spam list.

## 9 Value of the DNC list

One could estimate the value of the DNC list in a variety of ways. According to the FTC, prior to the its do-not-call registry, about 104 million telemarketing calls were attempted per day.<sup>28</sup> If each of these calls imposed, say, a net 10 cents worth of annoyance on the recipients, then this amounts to \$10 million per day, or about \$3.6 billion per year of annoyance.

Alternatively, one could argue that consumers could get themselves removed from most lists by sending a postcard to the Direct Marketing Association (DMA) or registering on the DMA website for \$5 per year, or by signing up on a state DNC list. Most state lists, the DMA list and the national DNC list are valid for 5 years. In that case the 7.5 million people registered on the DMA's list would cost consumers a maximum of \$7.5 million if each were to pay \$5 for 5 years on the list, or \$1 per year. About 48 million more people signed up on the national DNC list, which was free. If we assume that people were aware of their options prior to the FTC's DNC list—a heroic assumption to be sure—those additional 48 million people presumably valued the freedom from being called at something more than \$1 per year. However, the DMA reports 80% efficiency from the TPS list. If we assume a 100% efficiency by the DNC it would imply a lower bound for the value of \$1.25 per year. This would put an lower bound on the extra value of the DNC list at \$60 million per year.

To be sure, there is an enormous gap between \$60 million and \$3.6 billion. However, even the lower number indicates that the national do-not-call list has generated significant consumer benefits.

## 10 Conclusion

Consumers value their privacy, leading them to take actions to eliminate unwanted solicitations. This paper uses the results of a unique natural experiment where consumers blocked telemarketing calls by registering with the FTC's do-not-call list. Our analysis of these data identifies important factors related to signup frequencies and largely confirms intuition and a simple choice model of registration behavior.

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<sup>28</sup>*Notice of Proposed Rulemaking and Memorandum Opinion and Order*, dated September 18, 2002, pp. 6–7. Ideally we would like to have the number of *completed* telemarketing calls, excluding those, for instance, that were made to a non-working number.

We believe that there are lessons to be learned from the experience with do-not-call registries that will shed light on the effects of other privacy programs such as a do-not-spam registry. Individuals—and governments seeking to protect their citizens’ privacy—face a tradeoff: to allow unobstructed access to consumers’ portals or to attempt to filter incoming messages. By design, the FTC’s DNC list is a rather indiscriminate tool for blocking solicitations. It necessarily imposes costs on consumers in those instances, infrequent as they may be, where a voluntary transaction would otherwise occur. On the other hand, as long as the true social cost of access to consumers is not accurately born by the marketer, too many messages will be sent and receivers will bear too great a cost.

Filtering is one solution. Disconnection from the network is a more drastic measure. An intermediate strategy is to create a “gated community” of users that controls access through selective membership. Whichever of these approaches is adopted, the loss of social benefits in the form of network externalities derived by users, or of reduced costs made possible by scale economies in deploying services and distributing content, could be significant.

## A State List Details

Even before the introduction of the FTC DNC list, 27 states had their own DNC list. Table 22 shows a summary of the individual state lists in use by July 1, 2003.<sup>29</sup> The start date generally reflects when the list went live, but when that information wasn't clearly available the date reflects when the legislation was enacted. *Merged* indicates the imputed date that the state list was merged with the FTC list (blank means it was not merged). *DMA/TPS* refers to the states promoting signups for the Direct Marketing Association's Telephone Preference Service. The cost of signing up is there as an indication only since the terms vary greatly. Signing up for the TPS list is free via mail, but a \$5 charge is put on signups through the web.

Several of the most recent lists seems to have been enacted to support the FTC Do-Not-Call list. In effect these lists had as their main purpose to allow citizens to pre-register for the FTC list. California is definitely in this category, but it is likely the case for most lists added during 2003. Maine has been using the TPS list since 2001, but, as far as we can tell, they started taking pre-registrations for the FTC DNC list as well hence the two rows entries.

Table 23 summarizes the imputed size of the state lists that were merged with the national DNC list. The date of the merger is identified visually and the mean daily signup rate between July 10 and August 28, not including the day of the merger, is used as the baseline. The resulting number is then deflated by the average number of phone lines in the state and compared to the total number of households.

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<sup>29</sup>The information was compiled by looking at webpages and press releases regarding each list. A good starting point is <http://www.the-dma.org/government/donotcalllists.shtml>

Table 22: States with their own DNC lists.

State	Start	Merged	DMA/TPS	Fee
Alabama	6/29/00	20/8		free
Alaska	Nov'96			\$5-\$50
Arkansas	Jan'00	21/8		\$5/year
California	4/1/03	26/7		free
Colorado	7/1/02	28/7		free
Connecticut	1/1/01	22/8		free
Florida	Q2'99	9/8		\$10/\$5
Georgia	Jan'99			\$5
	Jan'99	8/10		\$5
Idaho	Jan'01			\$10/\$5
Indiana	1/1/02			free
Kansas	1/1/03	18/8		free
Kentucky	7/15/02	17/8		free
Louisiana	1/1/02			free
Maine	2003?	26/7		free
	Aug'01		Yes	\$5 online
Massachusetts	1/1/03	15/8		free
Minnesota	1/1/03	20/8		free
Missouri	7/1/01			free
New York	4/1/01	14/8		free
North Dakota	4/1/03?	9/8		free
Oklahoma	1/1/03	22/7		free
Oregon	Jan'00			\$6.50/\$3
Pennsylvania	4/2/02		Yes	\$5 online
Tennessee	7/1/00			free
Texas	1/1/02			\$2.25/number
Vermont	7/1/02		Yes	\$5 online
Wisconsin	1/1/03			free
Wyoming	Jul'01		Yes	\$5 online

Table 23: Proportion of households signed up to merged state lists.

Start Year	Cost of Signing up			Total
	Free	Fee	TPS	
2003	19.6% (6)			19.6% (6)
2002	45.1% (2)			45.1% (2)
2001	22.0% (2)		7.8% (1)	21.2% (3)
Earlier	1.3% (1)	2.4% (3)		2.3% (4)
Total	21.8% (11)	2.4% (3)	7.8% (1)	16.9% (15)

Number of observations (states) in parenthesis.

## B Data Collection and Variable Construction

We use information provided by the Melissa Data Corporation ([www.melissadata.com](http://www.melissadata.com)) to map phone exchanges into counties. Their “Telephone Database” also identifies exchanges that are associated with wireless services (*e.g.*, cellular phones, beepers). Recently, the North American Numbering Plan was extended to include “thousand block number allocation” which made distinct assignments of each of the ten blocks of one thousand possible numbers in an NPA-NXX group. As a result, some of the thousand blocks could be assigned to wireless services while others are assigned to fixed line services. Our procedure for removing wireless numbers ignores this possibility.

Table 24: Distribution of exchanges represented in the DNC list.

Exchanges with at least one number signed up		
Wired	92,695	72.1%
Wireless	35,841	27.9%
Total	128,536	100%

Collapsing the DNC phone numbers by county provides us with 3,185 observations (out of approximately 3,200 counties). Table 25 shows the distribution between wired and wireless DNC sign-ups based on the mapping from the Melissa Data.

Table 25: Distribution of DNC signups for wired and wireless exchanges. Aggregated by county.

	N	mean	sum	
Wired	3,185	15,123	48,165,480	82.4%
Wireless	3,185	3,232	10,294,702	17.6%
Total	3,185	18,355	58,460,182	100%

To form the DNC sign-up frequencies, we divide sign-ups by two denominators both taken from Census: the number of households in the county and the number of households with a fixed line. Figure 6 compares the proportion of total DNC signups to total number of households (per county) v. signups of fixed telephony numbers to households with a phone. There are a number of counties where the ratio of cellphone to landline DNC registrations are surprisingly high (as much as 33 times higher in one county). It is possible that this points to errors in the classification between fixed and wireless exchanges in the Melissa Data. There are also a number of counties where the signup rate is above 1 (37 and 17 for *all* and *wired* respectively). One obvious reason for this is that we have not corrected for the number of lines per household (and thus multiple signups per household). Correcting the signup on landlines for number or lines leaves us with 9 counties out of 3,113 that have signup rates in excess of 1.<sup>30</sup>

<sup>30</sup>Due to the limited number of observations on number of lines we are using state means which may be enough to explain these last oddities.

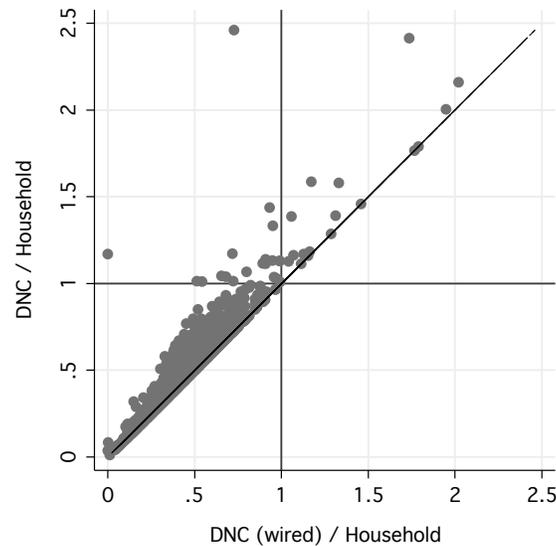


Figure 6: Plot of Total DNC Sign-ups per Household vs. Sign-ups of Land-lines per Household

We next use a telecommunications consumer survey provided by Taylor, Nelson, Sofres, the international market research firm. This survey is conducted by the TNS Telecoms division in cooperation with National Family Opinion’s national consumer panel. Data are collected quarterly on household purchases of many kinds of communications services and equipment, other household purchase decisions and attitudes, and detailed demographic characteristics. Each quarter has approximately 25,000 respondents. We draw on 10 quarters of the TNS Telecoms survey beginning in 3Q1999 and running through 4Q2000. This provides us with 256,312 observations for 49 states (including DC but excluding Alaska and Hawaii) and covers 3,024 counties.

We use these data to estimate the average number of fixed phone lines per household in each county as well as estimating Internet usage. For the represented counties, the minimum number of observations is 1 and the maximum 5,582 with a mean of 724.9 households per county. The mean Internet usage across these counties is 50.3% which is close to independent estimates of nationwide Internet use during the 1999–2001 time frame.

The TNST dataset also provide us with a count of fixed lines per household (set Table 26). On a state level we have number of lines per household ranging from 1.2 to 1.5 (mean of 1.22 and standard deviation 0.08). This figure is very close to the recently reported average of 1.24 fixed lines per household estimated by the FCC. Since the dataset did not include an observations from either Alaska or Hawaii we assigned them the mean of 1.22. In the end these data are only used in descriptive statistics (see, for example, Figure 3).<sup>31</sup>

We complement the TNST estimate of Internet usage with data drawn from the *Current Population Survey, August 2000—Internet and Computer Use Supplement*.<sup>32</sup> The CPS is based on 134,986 responses to a survey, of which 70,413 responded to the question “Does anyone in this

<sup>31</sup>We would like to include lines per household in our DNC estimations as an adjustment but are concerned with the lack of observations.

<sup>32</sup><http://www.nber.org/cps/cpsaug00.pdf>

Table 26: Number of fixed telephone lines per household. Source: TNST

# Lines	Frequency	Percent
0	6,872	2.7%
1	198,995	77.6%
2	42,579	16.6%
3	6,011	2.4%
4	1,855	0.7%
Total	256,312	100%
Mean	1.241	
Std. Dev.	0.525	

household use the Internet from home?” In this subsample, 79.9% of which answered affirmative. We are assuming that the CPS sample is essentially independent of the households sampled in the TNST data and aggregate the two datasets for our base Internet usage statistic by county.

After aggregation we are still left with a significant number of counties with no or very few observations. We assign the state average Internet usage to these counties. Rather than using a cutoff based on the number of observations alone, we looked at the difference between the county mean and the state-wide average divided by number of observations. If the difference was more than 2 percentage points, we replaced the county mean with the state mean. The breakdown can be seen in Table 27.

Table 27: Counties with measured vs. assumed Internet usage. Source: CPS, TNST

	Counties
Total Counties	3,200
Cty Mean Used	2,211
Imputed	989
Ir No State Mean	72
No County Mean	102
Diff > 0.02	815

We turn to the 2000 U.S. Census as the source for our household demographics.<sup>33</sup> In particular, Summary File 3 (SF3) reports 813 detailed tables of social, economic and housing characteristics compiled from a sample of approximately 19 million housing units (about 1 in 6 households) that received the Census 2000 long-form questionnaire.<sup>34</sup> We use these data aggregated at the county (*i.e.*, five-digit FIPS code) level.

Apart from demographics, we also use the SF3 Census data for the denominator in estimating

<sup>33</sup>We used the data prepared by ICPSR available at: <http://webapp.icpsr.umich.edu/cocoon/CENSUS-STUDY/13402.xml>.

<sup>34</sup><http://www.census.gov/Press-Release/www/2002/sumfile3.html>

DNC sign-up frequencies. In all of our models we use the number of occupied households per county. When we restrict ourselves to sign-ups of phone numbers corresponding to wired exchanges, we use households with a fixed telephone line as the denominator.

## C Summary Statistics

This section contains summary statistics for all variables by county. Population and Households are counts by county. Variables that are county-level statistics such as *HHSize\_Avg*, *HHInc\_Med* and *HVal\_Med* are reported as average or median values. All other variables are reported as proportion of households.

Table 28: Summary statistics for key variables

Variable Name	Mean	Std. Dev.	Min.	Max.
Population	90611.83	294411.59	444	9519338
Households	33977.75	104956.02	185	3136279
DNC landline	0.382	0.160	0.002	0.993
HasList	0.620	0.490	0	1
MergeList	0.280	0.450	0	1
Internet	0.486	0.129	0.038	0.868
HHRace White	0.870	0.149	0.069	1.025
HHRace Black	0.077	0.133	0	0.839
HHRace Native	0.016	0.064	0	0.920
HHRace Asian	0.006	0.018	0	0.479
HHRace Pac. Islander	0	0.003	0	0.087
HHRace Other	0.018	0.039	0	0.419
HHRace Multiple	0.011	0.011	0	0.200
HHLatino	0.045	0.104	0	0.974
HHAge 15–24	0.048	0.026	0	0.310
HHAge 25–34	0.145	0.031	0.055	0.385
HHAge 35–44	0.213	0.028	0.107	0.366
HHAge 45–54	0.198	0.021	0.108	0.322
HHAge 55–64	0.147	0.019	0.056	0.258
HHAge 65–74	0.128	0.027	0.031	0.274
HHAge 75up	0.121	0.037	0.011	0.262
HHSize=1	0.253	0.038	0.084	0.479
HHSize=2	0.347	0.036	0.122	0.506
HHSize=3	0.162	0.023	0.085	0.232
HHSize=4	0.138	0.021	0.066	0.244
HHSize=5up	0.100	0.034	0.044	0.457
KidsSub5	0.147	0.034	0.049	0.404
Kids5–11	0.244	0.050	0.111	0.765
Kids12–18	0.220	0.043	0.074	0.613
HHInc Median	35327	8827	15805	82929

*Continued on next page...*

... table 28 continued

Variable	Mean	Std. Dev.	Min.	Max.
HHInc 10dwn	0.121	0.050	0.016	0.362
HHInc 10-15	0.081	0.024	0.012	0.159
HHInc 15-20	0.078	0.019	0.014	0.151
HHInc 20-25	0.079	0.016	0.017	0.153
HHInc 25-30	0.075	0.013	0.022	0.130
HHInc 30-35	0.072	0.012	0.020	0.138
HHInc 35-40	0.065	0.010	0.018	0.134
HHInc 40-45	0.060	0.010	0.008	0.110
HHInc 45-50	0.052	0.010	0.014	0.105
HHInc 50-60	0.088	0.018	0.029	0.151
HHInc 60-75	0.090	0.025	0.02	0.174
HHInc 75-100	0.074	0.032	0.01	0.207
HHInc 100up	0.066	0.046	0.005	0.376
EduGrade	0.091	0.052	0.006	0.463
EduSomeHS	0.135	0.046	0.022	0.281
EduHS	0.348	0.065	0.109	0.532
EduSomeColl	0.262	0.056	0.099	0.449
EduColl	0.109	0.048	0.025	0.400
EduPostGrad	0.055	0.032	0.009	0.360
HHLingIso	0.017	0.030	0	0.339
OwnHome	0.740	0.075	0.195	0.899
HasMortgage	0.573	0.129	0.123	0.927
HHPoverty	0.142	0.062	0.022	0.485
UnmarriedPartners	0.043	0.015	0	0.153
NoMale	0.261	0.050	0.116	0.485
Urban Area	0.164	0.317	0	1
Urban Cluster	0.232	0.239	0	1
Rural Farm	0.040	0.043	0	0.324
Rural NonFarm	0.564	0.289	0	1
N		3094		