

The Demographics of the Do-Not-Call List

Data from do-not-call registries and other sources shows discernable patterns in the demographics of consumers who signed up for do-not-call lists. Such patterns might also be useful in analyzing the prospects for a do-not-spam registry.

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At least as far back as the first door-to-door salesman, consumers have had to deal with unwanted solicitations. Over time, new technologies have greatly expanded the portals into consumers' lives. Today, commercial and nonprofit interests can reach individuals through fixed and mobile phones, fax machines, traditional mail, email and Web cookies, and instant and short text messaging. While not free to the marketer, evidence suggests that access to these portals is under priced. The result has been junk mail, junk phone calls, junk faxes, and now junk email, or "spam."

In response, consumers have adopted strategies and technologies to limit privacy invasions. The simple answering machine, for example, can effectively screen telemarketing calls, as can calling features such as automatic number identification and call blocking. Use of these technologies represents an expression of consumers' demand for privacy. The federal do-not-call list has the potential to offer better privacy at a lower cost to the consumer.

Here, we describe our attempts to empirically measure consumer demand for protection from telemarketing phone calls. Our results have a direct bearing on the demand for spam protection, even though it's unlikely that a similar solution could be employed for email. Our work analyzes the pattern of consumer sign-ups with the US Federal Trade Commission's Do-Not-Call (DNC) registry, a centralized list of numbers that are blocked from non-exempt telemarketing calls.

Study overview

More than 60 million people have added their phone numbers to the DNC registry since it was launched in

2003. We view an individual's decision

to register with a DNC list as the outcome of an optimization problem: people maximize the call-blocking benefit, net the sign-up costs and purchases they might have otherwise made through a telemarketer. For their part, telemarketers make calls to maximize the call return, net their costs. Telemarketers tend to target individuals on the basis of demographic characteristics that affect their willingness to sign up. The sign-up decision thus depends on the phone-line owner's characteristics.

To understand such a decision, we merged the FTC's (redacted) phone numbers with household census and demographic information aggregated to the county level. We found that just a few variables can explain most of the DNC sign-up variance. Comparing DNC sign-up frequency across US counties against averages for demographic characteristics reveals both expected and surprising insights:

- Sign-ups increase as average household income and education increase.
- A county's racial, linguistic, and household composition go a long way toward explaining sign-up patterns.
- The head-of-household's age is also significant: young households have low DNC participation, while senior citizens register at a high rate.
- Internet access is not a good predictor of DNC sign-up frequencies.

Some states had DNC lists that predated the FTC list's launch. States that charged for registration experienced lower sign-up rates than those that offer the service for free. In addition to these findings, we were able to estimate

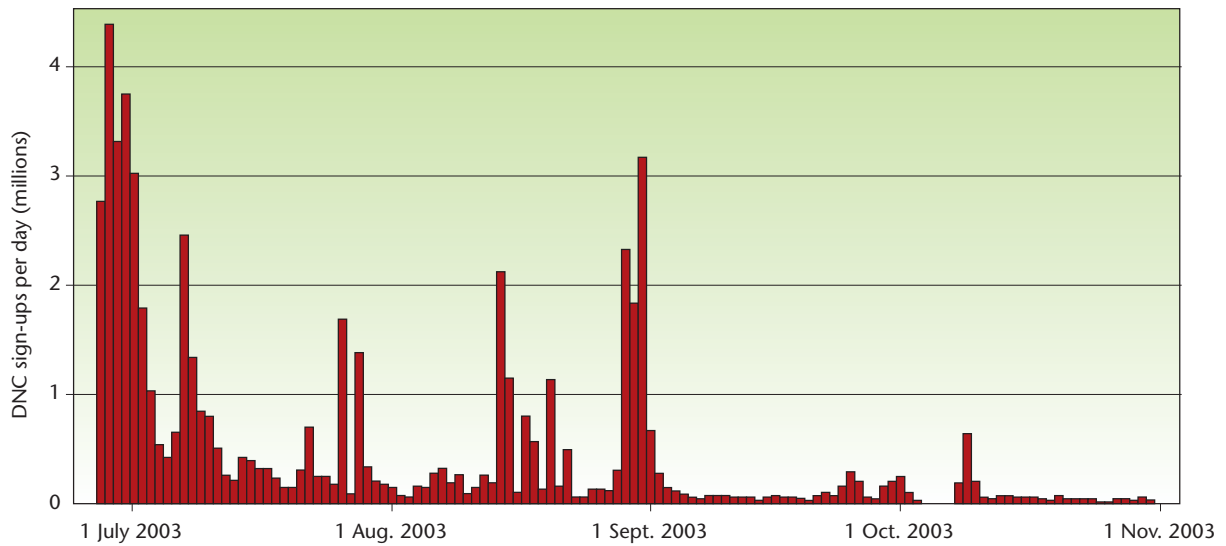


Figure 1. DNC sign-ups over time. Spikes occurred in the first week, as well as on 7 July, when consumers east of the Mississippi first became eligible. A spike prior to 1 September is likely due to consumers who wanted their number included when the list was activated on 1 October; those who registered after that date had to wait 90 days for the block take effect.

the DNC registry's monetary value to US consumers. While our estimates are crude (and the values' range is wide), such programs appear to have significant benefits.

We obtained redacted information on the nearly 60 million phone numbers entered into the FTC's DNC registry between 26 June and 1 November, 2003, including the time and date each number was registered. To ensure privacy, the FTC provided only the number's area code and exchange prefix (also called the "NPA-NXX" or "the exchange") in the dataset, and dropped exchanges with 10 or less observations from our analysis. To map the exchange to the county, we used a database purchased from the Melissa Data Corporation; this database is one that telemarketers often use themselves.

List characteristics

Figure 1 plots the number of phone numbers added to the DNC during the 129 days our study covered. The many sign-ups in the program's first few days suggest a pent-up demand for a DNC list. During the first week, only consumers in states west of the Mississippi (including Minnesota and Louisiana) could sign up using the toll-free number (though anyone could sign up over the Internet). As the FTC noted in a June 2003 news item (www.ftc.gov/ocr/ftcv2n6.htm), a spike occurred starting 7 July, the first day that states east of the Mississippi could register using the toll-free number. Another spike appears just before 1 September, 2003; sign-ups prior to that day were effective when the list went live on 1 October, 2003, while those after had to wait 90 days for the block to take effect.

The FTC registry is not the only, or the first, DNC list. When it was launched, 28 states had already provided some type of DNC list for their residents. Of these, 15 states eventually decided to merge their lists with the FTC's. States that declined to merge their lists typically run the lists in parallel. Several smaller spikes in the sample period come disproportionately from specific states. We used this correlation along with independent information to attribute each of 15 dates to the merger of a state list with the national list.

Although the DNC data consists of phone numbers, individuals (or, more likely, households) decide to register. Because both individuals and households often have more than one phone number (multiple fixed lines and cellular phones), we examined both the number of households per county and an estimate of the number of fixed lines per county as the denominator to form sign-up frequencies.

We first did a state-by-state analysis of DNC list responses. Figure 2 shows the proportion of household sign-ups, excluding numbers on nonwired exchanges and adjusting for each state's average number of household lines. The figure also indicates state-specific lists.

Five of the 28 states with their own DNC initiatives simply used the Direct Marketing Association's Telephone Preference Service (TPS) list, which charges consumers for registration. Six other state programs also charged for their service. Our results indicate that charging for a DNC list depresses the sign-up frequency. Of the DNC sign-ups during in our sample period, we attribute 11.8 percent to state-list mergers. Looking just at free

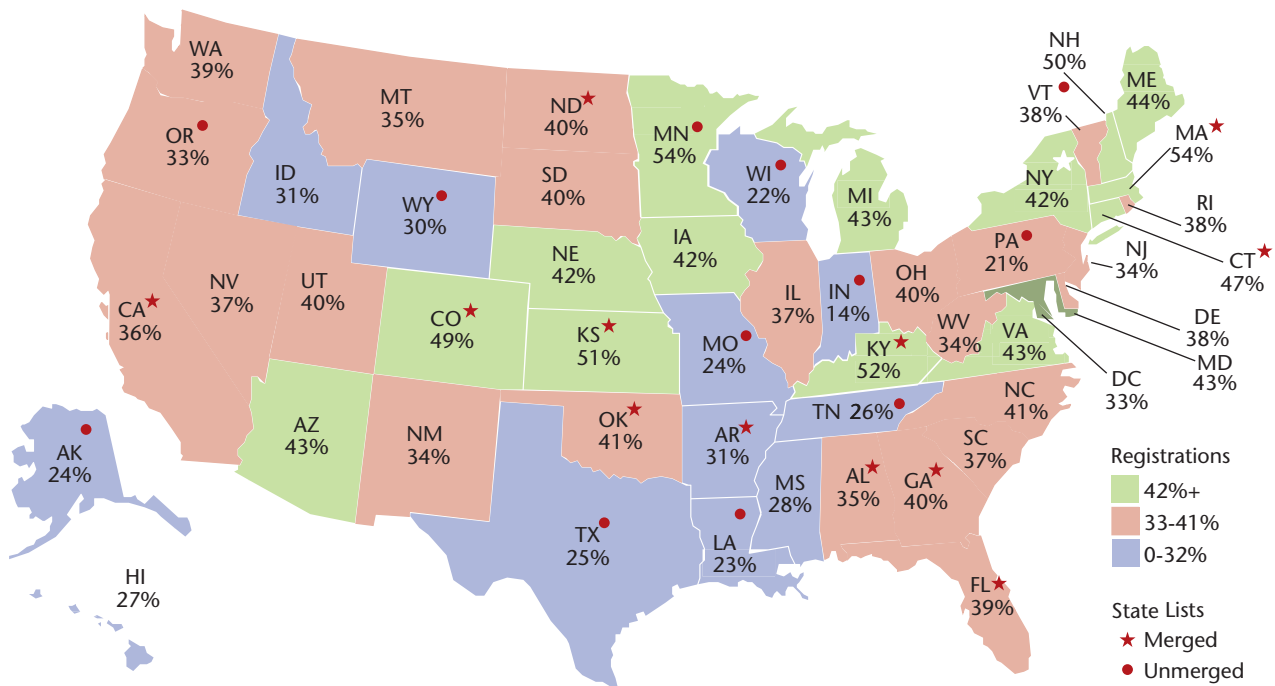


Figure 2. DNC registrations per household as of 1 November, 2003.

state programs, 14.3 percent of the sign-ups came from state lists. Compare that with 7.2 percent for states that used the DMA's TPS, and the mere 1 percent for those states that charged for sign-ups.

Demographic variables

We extracted most of our demographic variables from the 2000 census, including household income, size, race, and composition, as well as home value and mortgage. We supplemented this data with two other information sources: survey information from the US Census Bureau's Current Population Survey's household-level panels and TNS Telecom's ReQuest Survey dataset. We also rolled up those panels to the county level to generate the average Internet usage and lines per household. (A complete description of variable creations, data sources, and so on is available in a longer version of this article at <http://sims.berkeley.edu/~fredrik/research/papers/DncNber.pdf>.)

Our main demographics variables included

- the head-of-household's race, age, and education level;
- the number of children and their ages;
- the number of household members;
- whether or not an adult male lived in the household;
- whether or not it was a household of unmarried partners;
- household poverty status;
- whether or not there was linguistic isolation (lack of basic English skills);

- home ownership and mortgage status; and
- household income.

It's important to remember that our data is aggregated at the county level. Average income for an area does not necessarily capture the same information as the proportion of households in poverty in that area. Due to this aggregation, our analysis is limited to the likelihood of signing up given the county characteristics, rather than an individual household's characteristics.

Study results

In our analysis, we first look at the individual relationships between demographic categories and the observed frequencies of DNC sign-up. We follow this with a fully multivariate model of the sign-up decision.

Demographics and sign-up frequencies

We performed some simple regression analysis, examining individual demographic variables using the proportion of households within a county that fell within a given category. By assuming that a constant fraction of each demographic group signs up for each county's DNC list, we can set up a linear relationship in which each county's sign-up frequency is a function of the county's demographic groups. The regressions' coefficients should not be interpreted as the incremental effect of one variable, holding everything else constant. Rather, they should be interpreted as a marginal frequency distribution—how

Table 1. Households by race.

RACE	COEFFICIENT	STANDARD ERROR	MEAN
Caucasian	0.396**	0.004	0.870
African American	0.155**	0.019	0.077
Native American	-0.066	0.046	0.016
Asian	2.688**	0.218	0.006
Pacific Islander	-14.072**	1.422	0.000
Other	-0.499**	0.079	0.018
Multiple	2.125**	0.353	0.011

** indicates a significance level of 1 percent

Table 2. Household size.

SIZE	COEFFICIENT	STANDARD ERROR	MEAN
1	0.386**	0.072	0.253
2	0.753**	0.065	0.347
3	-1.454**	0.157	0.162
4	3.285**	0.280	0.138
5 and up	-0.823**	0.096	0.238

** indicates a significance level of 1 percent

Table 3. Internet access at home.

VARIABLE	COEFFICIENT	STANDARD ERROR	MEAN
Internet	0.431**	0.012	0.486
No Internet	0.335**	0.011	0.514
Difference	0.096**		

** indicates a significance level of 1 percent

we would expect sign-up frequency to change when we move between counties with different race distributions, where other variables (income, housing, age, and so on) also change. In cases where the coefficient is greater than one or less than zero, we simply indicate that the effect is “high” or “low.” These regressions are purely descriptive in nature, and should not be given a causal interpretation. We now highlight results of a few interesting variables (complete results are available in our extended article).

Table 1 shows how race affects sign-up frequency (normalized by household). Roughly speaking, it appears that 40 percent of Caucasians and 15 percent of African-Americans signed up, with low percentages of Native Americans, Pacific Islanders, and other races. However, a high percentage of Asians and multi-race households

signed up. This should be compared to the national average of 38.2 percent. Table 1’s “Mean” column indicates the fraction of the population that each demographic group represents.

Table 2 shows sign-up frequency as a function of household size, with two- and four-person households having a high sign-up probability. Curiously, households with five or more people seem to have a lower sign-up frequency. Perhaps larger households have a lower baseline privacy level, so the incremental amount that DNC adds to overall privacy is low. Alternatively, it might be that the annoyance caused by telemarketer’s calls is spread over a larger number of people.

Counties with a high percentage of Internet users tended to have slightly higher sign-ups rates (see Table 3).

Table 4. Urban and rural areas.

VARIABLE	COEFFICIENT	STANDARD ERROR	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
** indicates a significance level of 1 percent			

Also, while a high degree of urbanization increases the sign-up likelihood, farming communities tend to have the highest sign-up level (see Table 4).

A multivariate model of sign-up frequencies

For a more thorough analysis, we specified a choice model in which DNC sign-up decisions were a function of multiple demographics and statewide variables. Table 5 shows the regression results for several different model specifications. We report odds ratios (*e^b*) rather than straight coefficients (*b*). Significance tests (*t*) are similarly transformed (odds ratios measure variable’s impact on the relative odds of DNC sign-up. No effect is measured by an odds ratio of 1.) The Kitchen Sink model includes all demographic variables; the Parsimonious I and II models reduce the number of variables to isolate the most important ones. While we have no reason to expect states to be different from one another, we include state dummy variables as a proxy for other missing variables that could vary by state. The overall explanatory power of the models is reported with adjusted *R*².

Counties with higher income households have a higher probability of DNC sign-up. Not surprisingly, sign-up is negatively impacted in households with low education (did not finish high school) and linguistic isolation. It’s harder to explain the consistent positive impact of a county’s having a high proportion of Latino households. The effect of children is not easily explained. It’s possible that, with very young children, someone is more likely to be at home when a telemarketer calls. When teenagers are present, it’s possible that they frequently answer the phone and their annoyance is either not valued by or not reported to the adults making sign-up decisions. Unexpectedly, once we control for these other variables, Internet penetration does not make a significant difference on DNC sign-ups.

Perhaps the most interesting result is how much explanatory power we derived from only three variables: Income, presence of teenagers, and low education.

Comparing models that use only state-level variables, we found that these three variables raise the adjusted *R*² by 25 and 27 percent for models with and without state dummies, respectively. Even throwing in the full Kitchen Sink adds only an additional 5 to 6 percent.

Discussion

We can estimate a DNC list’s value in various ways. According to the FTC, prior to the DNC registry, about 104 million telemarketing calls were attempted per day.¹ If each of these calls imposed, say, 10 cents worth of annoyance on recipients, the costs would be US\$10 million per day, or about US\$3.6 billion per year.

Alternatively, we could argue that consumers can remove themselves from most lists in other ways: by sending the Direct Marketing Association US\$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 five years. Given that, if each of the 7.5 million people registered on the DMA’s list paid US\$5 for five years, consumers would spend a total maximum of US\$7.5 million. 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 US\$1 per year. The DMA, however, reports only 80 percent efficiency with the TPS list. If we assume the DNC achieves 100 percent efficiency, it implies a lower bound for the value of US\$1.25 per year. This would put a lower bound on the extra value of the DNC list at US\$60 million per year.

To be sure, there is an enormous gap between US\$60 million and US\$3.6 billion. However, even the lower number indicates that the national DNC list has generated significant consumer benefits.

How much consumers value their privacy in relation to unwanted solicitations varies by demographic

Table 5. Multivariate effects on sign-up frequencies.

	KITCHEN SINK		PARSIMONIOUS I		PARSIMONIOUS 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**	n/a	n/a
p[Kids under 5]	21.766**	5.784*	n/a	n/a	n/a	n/a
p[Kids 5–11]	0.148*	0.300†	n/a	n/a	n/a	n/a
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**	n/a	n/a
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*
K. Sink 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	3094	3094	3094	3094	3094

Significance levels are reported as follows: † : 10 percent * : 5 percent ** : 1 percent

characteristics in understandable patterns. We believe that the same would be true were a do-not-spam registry created. That said, a surprisingly large portion of the population does not find telemarketing calls and spam email to be annoying.^{2,3} While the likelihood that these solicitations result in a successful transaction is extremely low, it's not zero. This suggests that consumers in the aggregate place a value on these marketing channels. The FTC's DNC list is rather indiscriminate in its blocking of incoming calls, unlike, for example, automatic number identification or—in the case of email—a spam filter.

Individuals and governments seeking to protect citizens' privacy face a decision about whether to allow unobstructed access to their mailboxes or attempt to filter incoming messages. As long as marketers don't have to bear the true social cost of this access, too many messages will be sent and receivers will spend too much time and money dealing with them. The propensity to sign up for a do-not-spam list among demographic groups might well be similar that that observed for the do-not-call list. However, the do-not-spam list's popularity would depend critically on how well it worked, how it was implemented, and how it was enforced. □

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