Public Disclosure of Tax Information: Compliance Tool or Social Network?*

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Abstract

We conduct the first-ever study of actual searches done in a public tax disclosure system, analyzing about one million searches done in 2014 and 2015 in Norway. We characterize the social network these searches comprise, including its degree of homophily and reciprocation, and the demographics of targets and searchers. About one-fourth of searches occur within identifiable household and employment networks. Most searchers target people similar to themselves—*homophily* in network parlance—but young, low-income searchers also target older, successful people and celebrities. A causal research design based on the timing of searches relative to tax filing uncovers no evidence that, upon discovering they were targeted, targets subsequently increase their reported income. The evidence suggests that social comparisons motivate the bulk of searches rather than tax compliance. However, public disclosure may deter evasion even when compliance-motivated searches are rare in equilibrium.

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1. Introduction

Several countries offer their citizens the opportunity to learn about the reported income (and, in some cases, wealth) and tax liability of their fellow citizens. Public disclosure of tax return information is usually justified as helping to ensure better tax compliance and to make the tax system more transparent. Even if such tax policy objectives underlie public disclosure, citizens likely make use of the information to satisfy their curiosity about others as well as to benchmark their own financial and tax situations against others.

In this paper, we study the micro-structure of how people use public tax information. A recent literature, reviewed below, studies the impact of tax-return disclosure on a number of outcomes, but no research has examined who searches and who is targeted. This paper presents the first analysis of citizen-to-citizen search patterns, making use of newly available data from Norway. In Norway, with some limitations, people may search via the Internet to see what other Norwegians declare as taxable income, taxable wealth and tax liability. We obtained data on every search done in 2014 and 2015 querying tax year 2013 information—who searched for whom, and when. We merge this information with administrative records of individual demographic characteristics to construct a cross-sectional dataset of the network of all searches, allowing us a unique opportunity to study the nature and consequences of public tax disclosure. An important feature of searches done in this period is that the targets of searches could observe, by logging into their account on the tax authority's website, who had searched for them. Thus, they could reciprocate the search, and/or increase their reported income if they were concerned about whistleblowing that would reveal tax evasion to the authorities. Naturally, this fact also implies that our findings characterize searches under a non-anonymous search regime, and we do not know how the results would differ under anonymity.

We use descriptive and causal analysis to understand the main motivations for searches. Based on existing literature, we focus on two broad possibilities. First, individuals may use searches to facilitate social comparisons, which could explain the estimated effects of Norwegian public disclosure on subjective well-being (Perez-Truglia, 2020) and job quitting (Rege and Solli, 2013). Second, individuals may use searches to check whether others are truthfully reporting to the tax authority, which could explain the effects of public disclosure on tax reporting behavior (Bø, Slemrod, and Thoresen, 2015). We conclude that the bulk of searches are motivated by some form of social comparison.

As such, we also interpret demographic patterns in searches as informative about to whom individuals choose to compare themselves. Despite a large literature on social comparisons, the evidence on which actual individuals or groups form the basis for such comparisons is scant, consisting of only survey evidence (Clark and Senik, 2010, Perez-Truglia, 2020).[1] Our data provide a unique opportunity to shed light on this question with observational data.

We begin by characterizing in detail the social network these searches comprise and the characteristics of the individuals initiating a search (*searchers)* and the individuals whose information was queried by a searcher (*targets*). Our main findings regarding social comparisons involve the joint distribution of searcher-target characteristics. We find that approximately one-fourth of searches occur within identifiable household or employment networks. Searcher-target pairs are far more likely to have similar characteristics than two random individuals from the population of searchers and targets, for virtually any characteristic we observe, a property known as *homophily* in network analysis. Our findings of substantial searching within household and employment networks, and strong homophily are both consistent with the survey evidence on social comparisons in Clark and Senik (2010) and Perez-Truglia (2020). We also document that 6.3 percent of searches are reciprocated, meaning that the targets search for those who searched for them. Frequent reciprocity is reminiscent of the "reciprocity norms" studied by Cullen and Perez-Truglia (2022).

We document one further phenomenon in the data that is not covered by prior survey evidence: young, low-income searchers frequently target older, highly successful people and celebrities. Such searches are difficult to rationalize under the "relative income hypothesis" idea at the core of many papers on social comparisons (Duesenberry 1949, Luttmer 2005) because, according to this view, comparing to very successful individuals should confer significant disutility.[2] A natural alternative is that these searches by young, low-income workers for highly successful people and celebrities may be motivated by the "tunnel effects" hypothesis of Hirschman and

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[1] Interestingly, the title of a seminal work on social comparisons, Frank (1985), "Choosing the Right Pond," alludes to the fact that individuals may choose with whom to compare, but relatively little literature has explicitly studied how individuals make these choices.

[2] In other words, if individuals freely choose to whom they compare themselves, under the relative income hypothesis they will prefer not to choose highly successful people, as this establishes a high reference point against which they compare their own incomes (Reck and Seibold 2021).

Rothschild (1973) – i.e. searching role models whose income may be informative for one's own future income – or perhaps simple curiosity. [3]

We then turn to assessing the role of the disclosure system in ensuring tax compliance. We find that the tax information of self-employed people is, ceteris paribus, substantially more likely to be targeted. Given that in Norway third-party information reporting severely limits evasion possibilities for most employees, this suggests that potential whistleblowing is a non-trivial motivation for searching. Nevertheless, about 90 percent of searches target wage earners, who have little capacity for evasion. Finally, we conduct a causal analysis of how being targeted affects subsequent income reporting by targets. The research design leverages the fact that searches before tax filing in a given year can influence targets' reporting behavior in that year, while searches after tax filing cannot. We find small and insignificant effects of being targeted on tax reporting behavior, even for self-employed individuals. From this we infer that being targeted does not generate tax compliance for the vast majority of individuals.

Overall, the evidence suggests that much of the utility of public tax information to individuals derives from the opportunity to learn about the incomes of others for non-tax reasons, plausibly to engage in social comparisons or to satisfy other types of curiosity. This is consistent with survey evidence in Perez-Truglia (2020) finding that 77 percent of respondents searched for curiosity and just 2 percent for compliance monitoring. Notably, Bø, Slemrod, and Thoresen (2015) estimate that public disclosure in Norway did cause business owners to increase their reported incomes by about 3 percent.[4] However, this does not imply a contradiction in findings. For example, Amir, Lazar, and Levi (2018) studied a different whistleblower policy in Israel and reached a similar conclusion: actual whistleblowing was rare but the initial deterrence effects of the policy were nevertheless significant. In our case, much of the effect of public disclosure on tax compliance may be coming from the *availability* of

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[3] A small literature in psychology studies the relationship between celebrity admiration and subjective well-being, with a number of studies concluding that such admiration decreases well-being. For example, Aruguete et al. (2019) find that celebrity admiration is negatively correlated with some predictors of life satisfaction, but they find the opposite for a measure of curiosity, which predicts life satisfaction is positively correlated with admiration for celebrities.

[4] We note that the Bø, Slemrod, and Thoresen study covered a period when searches could be made anonymously, while this paper concerns a period after this anonymity had been removed. Similar studies examine the effects of tax return disclosure policies in Japan (Hasegawa et al. 2011), Australia (Hoopes, Robinson and Slemrod 2018), and Pakistan (Slemrod, Ur Rehman, and Waseem 2020), finding that such policies either improved compliance or induced taxpayers to take action to shield their income from disclosure.

information rather than whether information is actually used for whistleblowing in equilibrium.

2. The Income Tax and Public Tax-Return Disclosure in Norway

2.1 The Norwegian income tax system

Norway has a dual income tax system, with a graduated rate structure for labor income and pensions and a flat rate tax on capital income, as well as an annual wealth tax. Employers must withhold and remit tax for employees. In March or April following the tax calendar year, the tax authority provides people with a "pre-filled" tax return that lists what the tax authority knows from third-party information reports regarding income, deductions, assets, and debts. The taxpayer either accepts the return as provided, or makes adjustments to reflect their tax situation. Because the employer is responsible for reporting to the tax authority the salary paid to every employee, the opportunities for wage earners to underreport income are limited relative to the self-employed.

2.2 Public tax disclosure in Norway

Norway has a long history of public disclosure of information from income tax returns, going back at least to the middle of the nineteenth century. In earlier times, citizens could visit the local tax office or the city hall and look through a book that contained information about each taxpayer in the local area. Access was limited to regular working hours for three weeks after tax assessment was finished, usually in mid-October. Persons were listed by name and address, along with key measures from the income tax return.

In the fall of 2001, a national newspaper offered online access to tax information for the whole population through the web version of the newspaper, and soon all of the major national newspapers followed. Not long afterward, the Norwegian government regulated these searches. As of 2004, only the tax agency was permitted to publish the raw data. From 2004 to 2006, the searches were confined to three weeks following the release of the data, but the number of searches was not restricted. Beginning in 2011, individuals were required to log in to the tax agency's website to conduct searches through a personalized login system for accessing online public services, which involved a pin code and a password. Consequently, only Norwegian taxpayers could conduct searches after 2011. Searches were limited to 500 per month.

Beginning in October 2014, when tax records for the tax year 2013 were made available for searches, taxpayers could learn whether someone else searched for them, while previously searches were anonymous. On the website of the Norwegian tax authority one could access a list of who had searched for oneself. The end of anonymity corresponded with a drop of 88 percent in the aggregate number of searches.[5] The Tax Director of the Norwegian Tax Administration, Hans Christian Holte, characterized this change as "tak[ing] out the Peeping Tom mentality" and discouraging criminals from searching for wealthy people to target. He also stated, "We like people to do searches which could help us in investigating tax evasion and the amount of tips that we get has not gone down,"[6] implying that the authorities saw compliance-motivated searches as important, and that the deterrence function of disclosure was not diminished by the elimination of anonymity. Our dataset of searches comes from the period (immediately) after the abolition of the anonymity of searches. As we have no data on searches in the anonymity period, we do not know how the pattern of searches might be different in the prior regime.

Appendix A display screenshots of the query process on the tax authority's webpage. Upon logging in, individuals can search for others' information by first and last name, or last name and year of birth. They then select the individual they wish to learn about, and the website provides that person's reported taxable income, net wealth and assessed taxes.[7] Also available are birth year and the postal code and city of the individual's registered residence.

Because they are more likely to go online to alter their pre-filled return, as the pre-filled return would often not accurately reflect receipts and expenses, a self-employed person is probably more likely to notice that someone has searched for their information. Wage earners without self-employment income may log in to learn how much tax is due to be

[5] Ministry of Finance (2014), cited in Perez-Truglia (2020). As noted in Perez-Truglia (2020, fn. 20), some individuals started selling a search service to allow users to search under their names and thus effectively preserve their anonymity. One company offered an anonymous search for NOK950 (about $120) per search.

[6] Bevanger (2017).

[7] General income is a net income concept (taxed at 27 percent) including all types of taxable income, after the deduction of all deductible expenses. Net wealth is the basis for the wealth tax. Assessed tax is the sum of general income tax, surtax on personal income and wealth tax.

remitted or rebated, or to provide information that documents deductions. Overall, 93 percent of self-employed, but only 15 percent of employees, modify their returns to some degree.

3. Who Searches, and For Whom Do They Search?

We begin by characterizing the volume and nature of searches. We do so using data on all searches for tax year 2013, which was available for searches from October 2014 to August 2015. The total number of observations amounts to 1,316,091 searches. In calculating all the figures we report below, we make three sample selection restrictions. First, we drop any search observations where either the searching or target individual cannot be identified in the income registers, which accounts for 25,432 (1.9 percent) of searches. Second, we drop all but the first of multiple searches by the same searcher for the same target; this results in an additional 237,626 (18.4 percent) of searches being dropped. Almost half of the multiple searches appear on the same date, often within seconds of each other, and are likely to be instances of inadvertent re-clicking. Third, we exclude all searches by individuals who were less than 18 years of age in 2013, which amounts to 83,229 (7.9 percent) of the restricted sample of searches.[8]

These sample restrictions leave us with 969,804 searches between October 2014 and August 2015. To put this number into perspective, in 2013 the adult (18 and over) population in Norway was 3,983,896. Of the total number of searches, 262,078, or 27 percent, were the results of people searching for themselves.

3.1 Timing of search

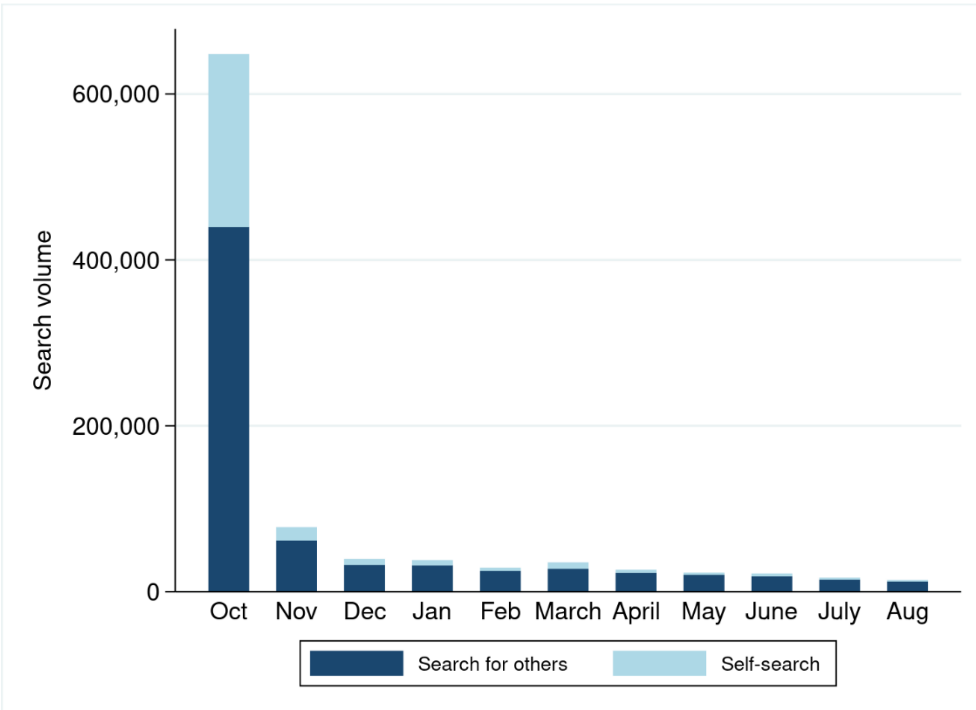
Figure 1 shows the distribution of searches by month in this period. A majority of the searches, 66.9 percent, occurred in the first month that information from the new tax year was available, October of 2014.[9] Self-searches are especially concentrated in October, suggesting that many people search for themselves to see what others can see about them, a phenomenon akin to Googling oneself. Figure B.1 in Appendix B reports more details on the exact date of searches, which reveals that, even within October, the number of searches is skewed to the opening of the search process. More than half--54 percent--of the October searches occurred on the first day that search was available,

[8] Individuals above the age of 16 years old can search, but only for individuals at least 18 years old in 2013. This asymmetry is the main reason we restrict attention to the 18-or-older searcher population.

[9] See Table B.1 in Appendix B.

October 17. There is also a slight blip up in March of 2015, when (on the 19th) the pre-filled returns for the 2014 tax year became available; some taxpayers were likely checking the 2013 information while logging in to view their own pre-filled tax information for 2014.[10]

Figure 1. Searches by Month in 2014 and 2015



Notes: This figure plots the number of searches conducted in each month for which tax year 2013 information was available, from October 2014 to August 2015, using the full sample of searches. Searches are divided into searches for one's own information and search for others' information.

3.2 Concentration of search

Because people can search for multiple targets, the number of searches overstates the number of distinct searchers and distinct targets. The number of searchers was less than one-third of the number of searches, 292,417, so that on average each searcher made approximately three searches. About 7.3 percent of the adult population did at least one search. Notably, almost all of the searchers also searched for themselves (262,078 individuals). The number of distinct targets was much higher, 735,071, or 18.5 percent

[10] Notably, 43 percent of searches on March 19th were the results of people searching for themselves (against 27 percent overall).

of the adult population. Of those, 561,116 individuals were targeted at least once by someone other than themselves.

Figure 2 provides information about the number and concentration of distinct searchers and targets. Panel A shows that 152,737 searchers (about half of all searchers) made only one search, and that 1,147 searchers (0.4 percent), searched for more than fifty different taxpayers.

Figure 2. Number of Searches per Searcher or Target

Notes: This figure plots the number of searchers and targets by the search volume per searcher or target. Searches are divided into searches for one's own information and search for others' information.

Panel B shows that the search targets are less concentrated than the searchers. Just under 80 percent of all targets, 581,254 to be exact, were targeted by only one searcher. Although less than 1 percent of all targets were targeted by more than three searchers, there are some "star" targets. 88 individuals were targeted by more than 50 Norwegians, and ten individuals were targeted by more than 500 individuals, with 1,087 Norwegians targeting the most "popular" Norwegian.[11]

3.3 Who searches and who is targeted by searches?

We next link the search data to demographic information in the population register in order to characterize who searches, and who is targeted. In addition to giving us a broad overview of the network of searches, the characteristics of searchers and targets also provide some insight into searchers' motivations for searching.[12] For example, if searches are related to interest in tax evasion, we should expect searches to target populations where tax evasion is more common, such as self-employed individuals.

Table 1 shows that those who target other people (labeled "searchers for others") are much younger, much more likely to be male and wage earner, and much less likely to be married or have immigrant status, compared to the adult population. They have slightly higher than average income, but are less wealthy. Nearly all of these statements also apply to self-searchers who, however, have notably higher income. If we limit our attention to those who do at least ten or more searches (not shown), we find that this group is even younger (30 years), more male (0.72), but are more likely to be an immigrant (0.13) and have lower education (11.9 years) and low income (44th percentile).

The last column of Table 1 presents the average demographic characteristics of those who were targeted at least once by someone other than themselves. Targets are younger than the average Norwegian, but older than the average searcher. Targets are about as equally male as the average searcher. They are more likely to be married: 43 percent of targets are married, compared to just 37 percent for those who search for others. Targets also have higher income compared to either searchers for others (but lower than self-searchers) or the overall population, and are more likely to be self-employed.

Table 1: Mean Characteristics of Searchers and Targets, Compared to the Overall Adult Population

	Adult Population	Searchers for others	Self-searchers	Targets of others

[11] Of the top 10, three are billionaire business people, three are politicians, two are bloggers, one is a singer, and one is an athlete.

[12] Note that, during this period, Internet penetration in Norway was 96 percent, so differential access to the Internet is unlikely to explain a significant amount of the demographic variation in search behavior. See https://www.statista.com/statistics/631917/norway-access-to-the-internet/.

Age	47.50	36.73	38.31	43.17
Male	0.50	0.63	0.66	0.61
Single household	0.26	0.35	0.37	0.29
Married couple	0.45	0.37	0.35	0.43
Years of education	12.06	12.55	12.75	12.39
Immigrant	0.14	0.09	0.07	0.10
Residence in densely populated area	0.30	0.32	0.34	0.31
Student	0.07	0.15	0.12	0.09
Wage earner	0.71	0.88	0.89	0.82
Self-employed	0.086	0.099	0.105	0.121
Unemployed/disabled/soc. welfare	0.14	0.10	0.09	0.10
Old-age pensioner	0.19	0.06	0.06	0.12
Income percentile	50.50	57.09	61.84	58.85
Wealth percentile	50.50	44.21	43.60	48.00
Number of observations	3,983,896	161,045	262,078	561,116

Notes: The table presents mean characteristics for the overall adult population and for three sub-populations: "searchers for others," "self-searches," and "targets by others." "Searchers for others" are individuals searching at least once for someone other than themselves. "Targets by others" are individuals who have been targeted at least once by someone other than themselves. "Self-searchers" are all individuals who searched for themselves. An individual may be present in more than one of these sub-populations. All reported characteristics are based on registered information from 2013. Male, single households and married couples are all indicator variables (0/1). Immigrants are defined in Norwegian registers as persons born abroad of two foreign-born parents and four foreign-born grandparents. Residence in a densely populated area is an indicator variable, which is 1 if the individual is registered as living in one of the five largest cities in Norway (or the area around these cities). Students are defined as those receiving grants from the State Educational Loan Fund ("Lånekassen"). Wage earners are defined as having positive wage income. Self-employed are defined as having non-zero income from self-employment. Unemployed/disabled/soc. welfare have positive income from at least one of these sources. Old-age pensioners have positive pension income from the National Insurance Scheme (age 67 and above). Gross income ("samlet inntekt") and net wealth ("netto formue") are used to categorize individuals into income percentiles / wealth percentiles based on the income/wealth distribution of the overall adult population.

Several of these characteristics are correlated, so we next look at multiple regression analyses of the association of search behavior with demographic characteristics, the results of which are shown in Table 2. Column (2) presents estimates from a linear probability model of whether someone does at least one search on someone other than themselves, as a function of their demographics.[13] Most of the demographic patterns apparent in the summary statistics shown in Table 1 are also visible in the multivariate

[13] Probit specifications yield qualitatively very similar results.

regression analyses. The probability of search declines with age, with a decreasing absolute slope. Men are 1.4 percentage points more likely to search than women, other things equal, and being married is associated with a 0.5 percent higher probability of search. A higher search probability has a positive partial association with both income and wealth. Being self-employed is associated with a 0.4 percent higher probability of doing at least one search. Column (3) of Table 2 shows that all of these patterns also appear when the dependent variable is the number of searches. Column (1) concerns self-searchers, where most but not all of the same patterns emerge. In contrast to search for others, married people and wage earners are less likely to self-search, while more educated people are more likely to do so.

Columns (4) and (5) of Table 2 present the results of who is targeted at least once by someone other than themselves, as well as how many times someone is targeted. The results confirm that higher-income individuals are more likely to be a target, other things equal; the estimated coefficient on income percentile in column (4) of Table 2 implies that the probability that someone in the 90th percentile is targeted is 13.4 percent higher (8 x 0.0168) than is someone in the 10th percentile. Comparing columns (2) and (4) of Table 2, we see that income is more strongly associated with being targeted than with searching: the estimated effect of income on being a target is almost three times higher than the estimated effect of income on the probability of being a searcher. Columns (4) and (5) also reveal that the self-employed are much more likely to be targeted, a topic we revisit below.

Table 2: Regression Analysis of Searcher and Target Characteristics

Dependent variable	(1) Self-searcher (0/1)	(2) Searcher for others (0/1)	(3) Searches for others (N|searcher)	(4) Targeted by others (0/1)	(5) Targeted by others (N|target)
Age/10	-0.0572***	-0.0493***	-3.9367***	-0.0898***	-0.3702***
	(0.0004)	(0.0004)	(0.2258)	(0.0006)	(0.0477)
Age, squared /1000	0.0376***	0.0350***	4.2064***	0.0703***	0.3290***
	(0.0004)	(0.0003)	(0.2797)	(0.0006)	(0.0504)
Male	0.0267***	0.0136***	1.6670***	0.0374***	0.0542***
	(0.0002)	(0.0002)	(0.0906)	(0.0004)	(0.0162)
Married	-0.0067***	0.0053***	-0.7412***	0.0116***	0.0243**
	(0.0003)	(0.0002)	(0.0841)	(0.0004)	(0.0117)
Years of education / 10	0.0048***	-0.0019***	-0.3541**	-0.0244***	-0.1654***

	(0.0005)	(0.0004)	(0.1569)	(0.0007)	(0.0332)
Immigrant	-0.0388***	-0.0213***	1.8689***	-0.0462***	-0.0476***
	(0.0003)	(0.0003)	(0.1128)	(0.0005)	(0.0080)
Residence in densely populated area	0.0030***	-0.0013***	0.2089**	-0.0014***	0.1122***
	(0.0003)	(0.0002)	(0.0947)	(0.0004)	(0.0168)
Student	0.0246***	0.0217***	-0.3403*	-0.0149***	-0.0009
	(0.0007)	(0.0006)	(0.1807)	(0.0009)	(0.0129)
Wage earner	-0.0046***	0.0005*	0.2008	0.0023***	-0.0162
	(0.0003)	(0.0003)	(0.1684)	(0.0005)	(0.0188)
Self-employed	0.0040***	0.0035***	0.1303	0.0429***	0.1982***
	(0.0005)	(0.0004)	(0.1035)	(0.0007)	(0.0339)
Unemployed/disabled/soc. welfare	0.0024***	0.0037***	0.3321	-0.0097***	0.0060
	(0.0003)	(0.0003)	(0.2174)	(0.0005)	(0.0099)
Old-age pensioner	0.0017***	0.0011***	-0.9207***	-0.0290***	-0.1234***
	(0.0005)	(0.0003)	(0.3060)	(0.0007)	(0.0235)
Income percentile / 10	0.0116***	0.0058***	-0.2223***	0.0168***	0.0564***
	(0.0001)	(0.0001)	(0.0272)	(0.0001)	(0.0050)
Wealth percentile / 10	0.0002***	0.0007***	-0.0020	0.0021***	0.0164***
	(0.0001)	(0.0000)	(0.0133)	(0.0001)	(0.0026)
Constant	0.1691***	0.1449***	12.8503***	0.3025***	1.8741***
	(0.0012)	(0.0010)	(0.4489)	(0.0017)	(0.0987)
Observations	3,983,896	3,983,896	161,045	3,983,896	561,116
R-squared	0.0424	0.0256	0.0141	0.0361	0.0022

Notes: This table reports the results of OLS regression analyses of searching or targeted individuals on observed characteristics of the searcher/target. The regression sample is the overall adult population (at least 18 years old). In column (1), the dependent variable is 1 if searched for themselves, and 0 otherwise. In column (2), the dependent variable is 1 if searched at least once for someone other than themselves, and 0 otherwise. In column (3), the dependent variable is the number of searches (excluding self-searches) an individual conducted, given that the individual searched at least once. In column (4), the dependent variable is 1 if targeted at least once by someone other than themselves, and 0 otherwise. In column (5), the dependent variable is the number of times targeted (excluding targeted by self-search), given that the individual was targeted at least once. All individual characteristics are based on registered information from 2013. See the note to Table 1 for details on the construction of the right-hand-side variables. Standard errors are provided in parentheses below point estimates. * p<0.10, **p<0.05, ***p<0.01.

4. Who Searches for Whom?

4.1 Search within identifiable social networks of households and employment

We now look more closely into the joint distribution of searcher and target characteristics, beginning by describing searches occurring within identifiable household or employment networks.

We find that, out of 707,726 searches for others, 86,851 searches (12.3 percent) occurred within households.[14] Of the number of distinct searchers (161,045 in total), 69,360 searched for a member of their own household, and 122,785 searched for someone outside of their household. Of the number of distinct targets (561,116 in total), 84,386 were targeted by a member of their own household, and 492,179 were targeted by someone outside of their household.[15] A regression analysis (not reported) of searches within households reveals that women are more likely to be targeted by spouses, but not generally. Notably, income matters a lot less for spousal searches.

We find that 15.9 percent of searches for others occur within an employment network.[16] Overall, 25.9 percent of searches (excluding self-search) occur within identifiable networks of either household or employment.[17] More details on how search within identifiable networks of household and employment is distributed over age and income are provided in Figure C.1 in Appendix C. One notable finding is that the very youngest (below age 25) and mid-age (peak 50-60 years old) individuals search relatively more often within-household,[18] whereas within employment network searches are mostly concentrated in the age group 20-50.[19]

4.2 Homophily in search

A ubiquitous finding about other social networks, such as networks of friends, is that people tend to be more frequently linked to others that are similar to themselves, a network characteristic called homophily.[20] Substantial homophily in the tax search network implies that different groups are isolated from each other and thus may acquire only "local" information—information on people like them—about reported income and wealth. We test for homophily along several dimensions, and begin with binary homophily, where each searcher and target is defined as being in one of two categories. In these analyses, we exclude self-searches and household searches. Table 3 summarizes

[14] Within-household searches consist of persons resident in the same dwelling and related to each other as spouse, registered partner, cohabitant, and/or parent and child (regardless of the child's age).
[15] The sum of the two categories exceeds the total because someone could have been targeted by a household member and by a non-household member.
[16] Employment networks are established based on information about all employers for each individual in 2013 (the tax year) and 2014 (the search year). If any of the employers are the same for the searcher and the target, it is regarded as a search within an employment network.
[17] When excluding searches within households, 15.5 percent of searches occur within employment networks.
[18] Note that parents and children are more likely belonging to the same household when the child is below age 25.
[19] One motive for search could be to learn about the income of potential employees or home renters. Unfortunately, we are limited in our capacity to infer from the data whether a search occurs for this particular reason.
[20] McPherson, Smith-Lovin, and Cook (2001).

these results, by comparing the actual observed probability of a given searcher-target identity compared to the probability of a random pair of a searcher and target in our sample.[21] The fourth column shows the ratio of the observed probability to the random probability. The higher is that ratio, the greater is homophily. Note, though, that these ratios cannot always be meaningfully compared across the rows that represent characteristic categories, because for well-represented groups this statistic cannot greatly exceed one. The final two columns reports the odds ratio and the log odds ratio, respectively.

Table 3 reveals that Norwegians are much more likely to search for tax information about people who live within their own municipality. As many as 45.8 percent of searches (excluding self-search and search within the same household) are for people who live in the same municipality, compared to just 3.3 percent of random searcher-target pairs. A highly intensive dimension of binary search homophily is by employer. While random searcher-target pairs have the same main employer just 0.1 percent of the time, 9.2 percent of such pairs are between pairs of people with the same main employer, over hundred times more likely than random. Age, immigration status, and both education field and level also exhibit substantial search homophily. Figure C.2 in Appendix C provides further graphical evidence of homophily in search by age, education level, income and wealth.

Table 3: Homophily in Search

	Observed probability	Random probability	Percentage point difference	Ratio	Odds ratio	Log odds ratio
Both male	49.4	46.8	2.7	1.1	1.1	0.11
Both female	12.6	10.0	2.6	1.3	1.3	0.26
Same municipality	45.8	3.3	42.5	14.0	24.8	3.21
Same age	19.7	6.5	13.2	3.1	3.5	1.26
Both immigrants	6.0	1.1	4.9	5.6	5.7	1.75
Neither immigrants	85.4	80.5	4.9	1.1	1.4	0.35
Both students	4.3	2.0	2.3	2.2	2.8	0.78
Neither students	73.3	70.9	2.4	1.0	1.3	0.12

[21] We estimated confidence intervals of the probability in the random searcher-target pair sample by 500 bootstrap replications. These estimated confidence intervals are very small. For example, for "both male" we find that the random probability is within the range (46.7, 46.9) with 95 percent certainty. From these estimates, we infer that there is statistically significant evidence of homophily in all of the dimensions considered in Table 3.

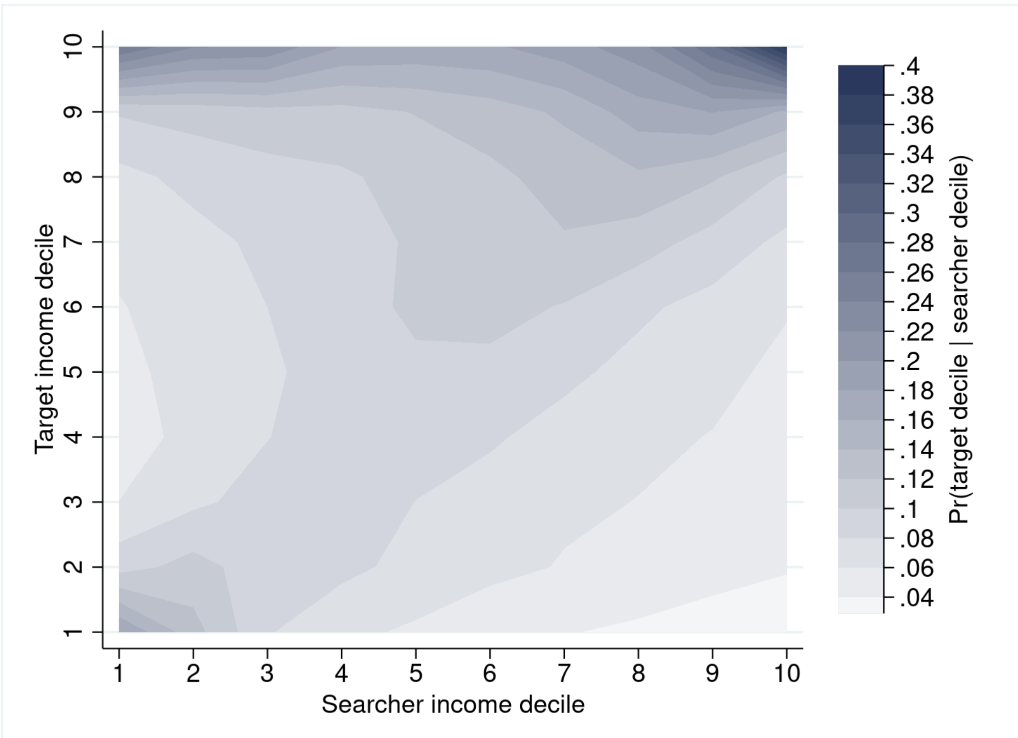
Both self-employed	2.1	1.1	1.0	1.8	2.1	0.75
Neither self-employed	79.8	78.8	1.0	1.0	1.1	0.06
Same main employer	9.2	0.1	9.1	152.5	101.2	4.62
Same employment network	15.5	0.2	15.3	79.2	91.8	4.52
Same education level	33.1	22.5	10.6	1.5	1.7	0.53
Same education field	14.8	8.4	6.4	1.8	1.9	0.64
Same education field and level	8.1	2.8	5.3	2.9	3.1	1.12
Same income level	15.9	9.9	6.0	1.6	1.7	0.54
Observations				620,875		

Notes: This figure reports the probability that searcher and target share a given characteristic for several different characteristics. The first column reports these probabilities in the population, excluding self-searches and searches within a household. We contrast this with the probability that a random pair of searchers and targets share this characteristic in the second column. This means that, for example, because there are many more male searchers and targets in the data, the probability of a random female-female pair is less than 0.25, and the probability of a random male-male pair is greater than 0.25. The ratio is defined as p_{obs}/p_{ran}, and the odds ratio is defined as $(p_{obs}/(1-p_{obs}))/(p_{ran}/(1-p_{ran}))$ where p_{obs} is the observed probability and p_{ran} is the random probability. Same age is defined as the target and searcher age being 1 year apart or less (in either direction). Education level has 9 categories. Education field has 7 categories (excluding "general" and "unknown"). Same income level is defined as less than a 5-percentile difference between searcher and target income rank. Information about the employment network is established based on information about all employers for each individual in 2013 and 2014. If any of the employers are the same for the searcher and the target, it is regarded as a search within the same employment network.

4.3 Beyond homophily

Figure 3 depicts the distribution of target income conditional on searcher income with a heat map, allowing one to go beyond just the mean of target income conditional on searcher income. It shows that low-income people mostly search for other low-income people and very high-income people. There is a very low probability of search in the bottom-right quantile of the graph: high-income people rarely search for low-income people. The bimodal distribution of target incomes conditional on low searcher income is the most significant instance we see of non-homophily. Overall, searcher and target characteristics are correlated, but at the bottom of the income distribution we also observe the opposite. This bi-modality is virtually entirely driven by the propensity of *young* and low-income searchers to target high-income targets (see Appendix Figure B-4). The heat map of Figure 3 summarizes a key finding of our paper: everyone searches for people similar to themselves, perhaps in their social network, but young, low-income people also disproportionately look up highly successful people. Relatedly, Figure C.3 in Appendix C shows that searches for stars in the network are also more common among young people at the bottom of the income distribution, where a star is defined as someone targeted by at least 50 searchers. We observe that 8-10 percent of searches done by the youngest or lowest-income searchers target stars, compared to less than 2 percent of searches for most other groups.

Figure 3. Heat Map of Searcher and Target Income



Notes: The figure presents a heat map of the distribution of target incomes conditional on searcher income. Darker colors represent higher probabilities for searching for targets of the given income decile, within the given searchers' decile. The income of searchers and targets are categorized into income deciles (1-10) defined by the overall adult population.

4.4 Reciprocal searching

The reciprocal nature of searches is of interest in part because it has been shown to affect the ability of a group to monitor and enforce behaviors. Excluding search within households, in 6.3 percent of searches the target subsequently searched for the searcher. This compares to a random searcher-target pair occurring in 0.11 percent of cases, so that reciprocal searching was approximately 60 times more likely than random. Notably, 44.5 percent of reciprocal searches occur on the same date (as opposed to 11.4 percent for a random searcher-target pair), and 70 percent of reciprocal searches happened within 4 days (compared to 27.4 percent for a random pair). We further find that the probability of reciprocated searches is increasing with the searcher's income, and that a larger share of reciprocated searches occur within employment networks or between individuals with the same education field; for more detail see Figures C.4 and C.5 in the Appendix.

5. Tax Disclosure and Tax Compliance

One important justification of public disclosure of tax returns is that it constrains tax evasion, because potential evaders are concerned that others will learn of suspiciously low reported income (or wealth) and report their concerns, and perhaps supporting evidence, to the tax authorities—i.e., they will become whistleblowers. The fact that we find strong evidence of homophily is not inconsistent with whistleblowing-motivated search happening, as potential whistleblowers may have more information about, and more interest in monitoring, people like themselves. A small-town hair salon owner may be especially interested in discovering whether her principal local competitor is gaining an unfair competitive advantage by evading income taxes.[22] Clearly, however, the evidence we have described in this paper thus far suggests that enforcing tax compliance is not the only motivation to search the publicly available tax information. For example, the fact that many Norwegians, and especially young, low-income people, often search for information about celebrities is unlikely to reflect tax compliance concerns.

[22] It is conceivable that the public disclosure scheme erodes tax compliance by facilitating a race to the bottom—learning about the surprisingly low reported taxable income tax someone else is apparently "getting away with" could induce more aggressive tax reports by the searcher. This avenue of influence has not been pursued in the literature, and we are grateful to a referee for suggesting it.

There is, though, credible evidence from other research—including about Norway—that public disclosure of tax information increases tax compliance of those with significant latitude for tax evasion, in particular self-employed people. The effect on tax compliance likely comes from the perceived *threat* of whistleblowing, which is not well measured by the extent of such information provided in equilibrium or the number of investigations or the volume of revenue collections directly tied to information from whistleblowers.[23] Indeed, a well-known feature of many game-theoretic models is that, in equilibrium, agents may never follow through on a threat if other agents believe that the threat is credible and respond accordingly. More concretely, Kleven, Kreiner, and Saez (2016) describe a model where a whistleblower threat deters tax evasion but, in equilibrium, whistleblowing seldom occurs. Nevertheless, it is of interest to analyze these data to assess the extent to which searches are motivated by concerns about the tax compliance of others, and to what degree being targeted for a search increases tax compliance.

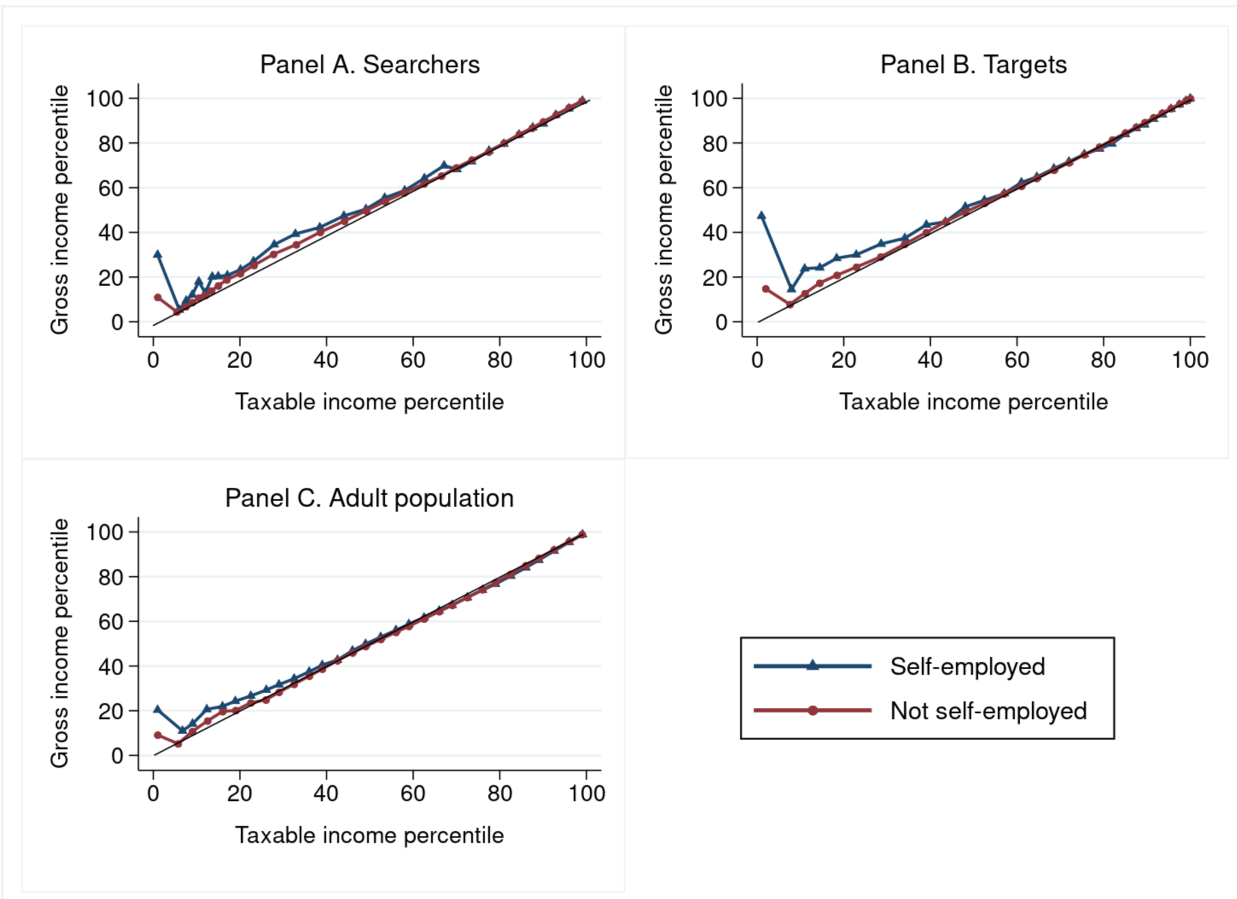
5.1 How much search is tax-motivated?

In Norway, as in most developed countries, third-party information reporting severely limits evasion possibilities for most employees, but not nearly as much for the self-employed, as the results of Bø, Slemrod, and Thoresen (2015) suggest. From Table 1, self-employed people comprise 12.1 percent of targets and just 8.6 percent of the adult population. Assuming compliance-related searches target only self-employed people, the fraction of such searches is at most 12.1 percent. Naturally, some self-employed people are certainly targeted by searchers with motives unrelated to whistleblowing. To account for this in a rough fashion, recall that the fourth column of Table 2 shows that a self-employed person has a statistically significant 4.3 percentage point higher probability of being targeted, other characteristics held fixed. If we interpret this to mean that the counterfactual targeting of self-employed people would be 7.8 percent (12.1 minus 4.3) in the absence of tax-compliance-related search, we would conclude that at most 4.3 percent of all searches in Norway were tax-compliance-related.

[23] Information on the extent and nature of whistleblowing would, nevertheless, be of substantial interest. We requested, alas unsuccessfully, data about tax evasion tips in Norway.

In sum, the fact that self-employed people are substantially more likely to be targeted is consistent with the idea that potential whistleblowing is a non-trivial motivation for searching. At the same time, we conclude that the great majority of searches of the public disclosure system are not motivated by potential whistleblowing. This does not necessarily indicate that the deterrence effect of *potential* whistleblowing is small.

Figure 4: Gross Income vs Taxable Income for Searchers, Targets and the Full Population



Notes: The panel presents binned scatterplots of individuals' gross income percentile by the same individuals' taxable income percentile. Panel C presents figures for the overall adult population (at least 18 years old), whereas Panel A and Panel B restrict attention to searchers and targets, as defined above. All panels include separate binned scatterplots for self-employed and not self-employed individuals (everyone not self-employed), where self-employed are defined as individuals with non-zero (positive or negative) income from self-employment.

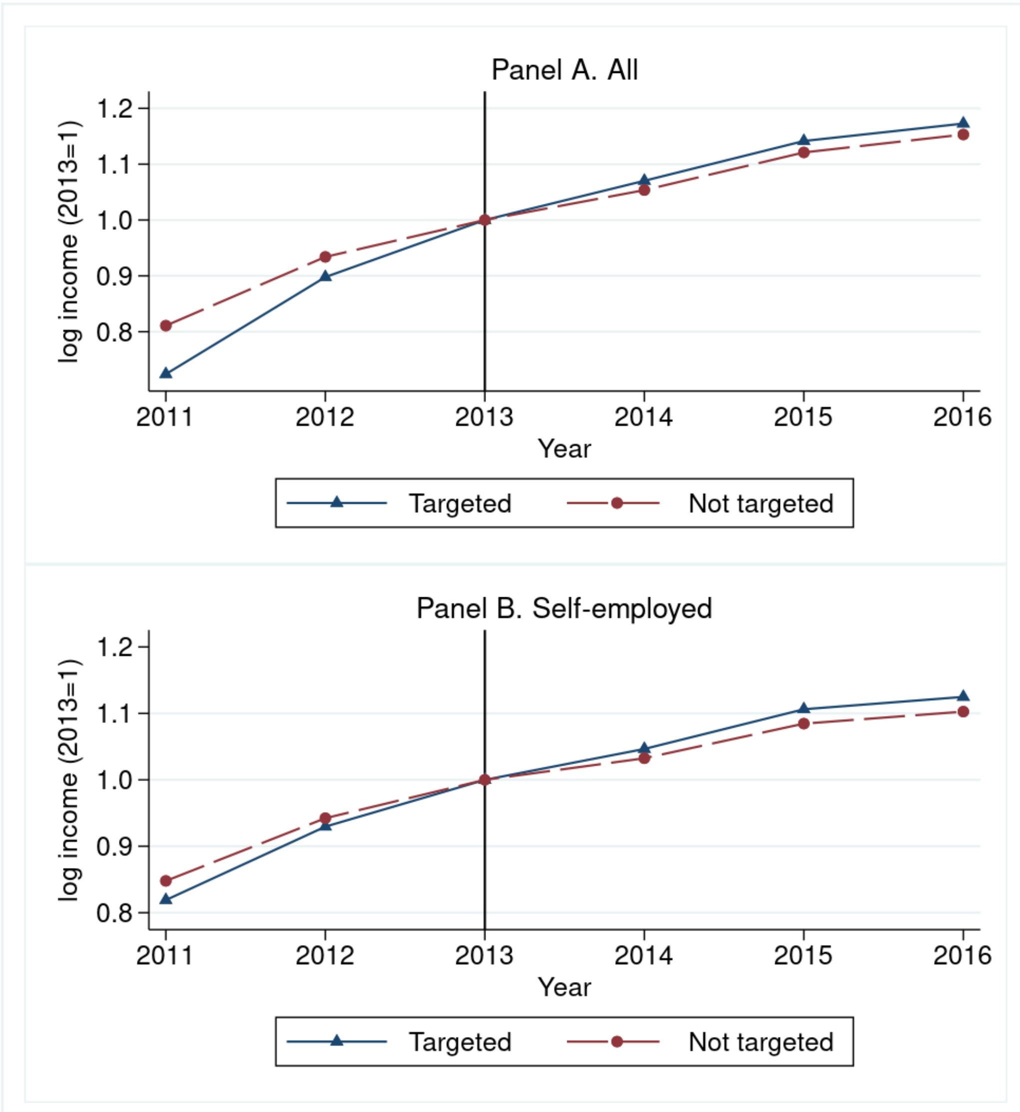
We have one further piece of evidence of the role of compliance-related searches. Our focus so far in this paper has been on reported gross (i.e., before deductions) income, but self-employed people have much more latitude to deduct certain expenses to obtain a lower taxable income. Figure 4 demonstrates that self-employed taxpayers have more possibilities to deduct expenses to obtain a lower taxable income, compared to the case for non-self-employed taxpayers. As Panel B shows, this is especially the case for self-employed targets, which is consistent with people searching more often for people with relatively low reported *taxable* income, which may possibly indicate tax evasion or avoidance in the form of overstated deductions.

5.2. Does being targeted change tax reporting behavior?

Getting searched may send a message to some targets: "I'm watching you." It might suggest that whistleblowing will ensue, depending on what is learned from the search and what is already known by the searcher about the target. In the absence of micro data on whistleblowers, we cannot directly study the connection between information search and subsequent whistleblowing activity. We can, though, analyze whether targets' tax reporting behavior changes after being targeted, recognizing that a change in reported income reflects both any change in true income as well as any change in the extent of non-compliance. For this analysis, we exclude self-searches and searches between individuals living in the same household.

We begin by examining aggregate time-series data on reported income for search targets versus non-targets. The upper panel of Figure 5 demonstrates that the trends of income reporting are slightly different between those targeted and not targeted throughout our period of observation. Apparently, searchers tend to target those whose income is growing faster than non-targets. We do not see any particular departure from prior trends in 2014, which is suggestive of little to no causal effect of being targeted on tax reporting behavior. In the lower panel of Figure 5, we condition on both targeted and not-targeted individuals being self-employed in 2014, thus focusing on the group for whom a causal tax compliance effect of being targeted is more likely (because tax noncompliance is more likely). Conditioning on being self-employed eliminates some (but not quite all) of the differential trend between the targeted and not targeted before 2014, but we still see no differential break from trend after 2014. In short, we are unable to entirely rule out selection bias in an analysis comparing those who are and are not targeted for search, but the results suggest that the causal effect of interest, if it exists, is likely small.

Figure 5: Time-Series Plots. Targeted versus Not Targeted.



Notes: This figure displays the evolution over time of the mean of log income in the given year for targets and non-targets. To make the time series comparable, we subtract from each series the mean of log income in 2013 and add 1. Panel B does the same analysis restricting to individuals who were self-employed in 2013. We add a black vertical line at 2013. Tax reporting in 2013 or earlier happens before searches occur while reported income in 2014 and later can possibly be affected by being targeted.

We next implement a more sophisticated causal design to test for compliance effects. We address the potential selection bias from comparisons between those targeted and others by examining the change in reporting behavior only of those taxpayers who were targeted by a search, differentiated by the *timing* of the search. In particular, we examine whether the first search for a taxpayer occurred before or after when the tax return was filed.

The idea behind this design is that, if a search occurs before filing, the taxpayer upon logging on to observe, and perhaps adjust, her pre-filled return would be able to see that the search has occurred and respond to this information, potentially by increasing reported income net of deductions. If, on the other hand, the search occurs after filing, it would be too late to increase reported income (for the current tax year). Our identification strategy presumes that the nature of searches and targets of searches occurring before or after filing are otherwise comparable, an assumption we can explore with placebo tests and pre-trend analysis.

Table 4 shows the results of a regression specification designed to reveal the effect of being targeted on the tax year 2014 income report. We restrict the sample to only those individuals whose 2013 tax information was targeted by a search for the first time either within two months of the 2014 tax return filing date (before or after), to minimize the possibility of selection bias based on the timing of search. We estimate a regression with individual and year fixed effects, where the dependent variable is the log of reported taxable income, first for all individuals, and then separately restricting the sample to self-employed individuals. Observations with zero or negative values for reported income in any year are discarded, so the regression includes only individuals declaring positive income in each tax year, from 2011 to 2016. We include individual fixed effects to account for the fact that the timing of search may be correlated with unobservable determinants of income; no interactions referring to 2013 are included, so estimated coefficients refer to the effect relative to 2013.

Table 4: Regression Analyses of the Effect of Being Targeted on Reported Income

	(1)	(2)	(3)	(4)
Dependent variable		log taxable income		
Sample	All	Self-employed	All	Self-employed
Year 2011 * targeted before filing	0.0070	0.0219		
	(0.0103)	(0.0222)		
Year 2012 * targeted before filing	-0.0033	0.0213		

	(0.0083)	(0.0185)		
Year 2014 * targeted before filing	**0.0000**	**0.0110**		
	(0.0077)	**(0.0185)**		
Year 2015 * targeted before filing	-0.0050	0.0053		
	(0.0091)	(0.0198)		
Year 2016 * targeted before filing	-0.0030	0.0022		
	(0.0099)	(0.0214)		
Year 2011 * targeted before deadline			0.0050	0.0012
			(0.0104)	(0.0234)
Year 2012 * targeted before deadline			-0.0052	0.0126
			(0.0084)	(0.0205)
Year 2014 * targeted before deadline			**-0.0027**	**0.0183**
			(0.0078)	**(0.0195)**
Year 2015 * targeted before deadline			-0.0061	0.0136
			(0.0092)	(0.0211)
Year 2016 * targeted before deadline			-0.0020	0.0315
			(0.0100)	(0.0232)
Year fixed effects	yes	yes	yes	yes
Individual fixed effects	yes	yes	yes	yes
Number of observations	339,316	37,237	338,305	36,566
R-squared	0.0091	0.0088	0.0090	0.0091

Notes: This table reports the results of regression analyses examining the effect of being targeted on reported income. The regression sample includes all individuals targeted for the first time within the time window of +/- 60 days around the filing date (columns 1 and 2) or the deadline for filing (in columns 3 and 4). Self-employed are defined as individuals with non-zero (positive or negative) income from self-employment in year 2013. The dependent variable is the log of taxable income ("*alminnelig inntekt*"), which is the tax base for income taxes.

The effects of interest in Table 4 are the year dummy variables interacted with the variable *targeted before filing*, which is a dummy variable that takes a value of one if the first search for tax year 2013 information was conducted in the two-month window before the filing date for tax year 2014, and zero if the search occurred in the two-month window after the filing date. If being targeted before filing increases reported income in 2014, we would expect to see that the estimated coefficient on the interaction term to be higher in tax year 2014 than in other years. Note that, in tax years before 2014, the taxpayer could not know whether she had been targeted in the later year, so the pre-filing versus post-filing behavior would not be affected by being targeted. Observing whether these effects are statistically different from zero is a pre-period test of the validity of the research design: if there are confounding differences between those targeted before or after filing throughout the period, these are likely reflected in pre-period trends in income (as in Figure 5).

Table 4 reveals that the causal effect of being targeted on income reporting is small and statistically indistinguishable from zero.[24] The point estimate for the self-employed is positive, as a compliance effect would suggest, but the *t*-statistic attached to this estimate is barely above one, and the point estimate is small, suggesting that being targeted increases incomes by perhaps 1.1 percent for the self-employed. As we discuss further in Appendix D, a potential concern with the specification in the first two columns of Table 4 is that the timing of filing is endogenous. We address this concern with an instrumental variables design leveraging the fact that searches after the filing deadline could not affect the timing of filing. Columns (3) and (4) of Table 4 report the reduced-form result for this IV design, and Appendix Table D.1 reports additional results. The IV results imply a similarly small effect of being targeted on reporting behavior, even for the self-employed.

In sum, neither our analysis of the aggregate time series nor a causal analysis of the micro search data generate compelling evidence that being targeted increases reported incomes. Taken together with the results of Section 5.1 about the lack of prominence of searches for those with more easily evadable self-employment income, we cannot confidently ascribe to many individual searches a compliance-increasing intent or outcome. As discussed above, this conclusion is not necessarily inconsistent with the findings of other research that the public disclosure *system* increases compliance because the compliance effect of this system on tax compliance may derive from the *availability* of information rather than the extent to which this information is actually accessed in equilibrium.

6. Conclusions

In this paper we shed light on the motivation for, and consequences of tax searches by undertaking the first-ever analysis of the actual searches done in a public tax disclosure system, comprising over one million searches done in 2014 and 2015 n Norway. We find that about one-quarter of searches occur within identifiable social networks of households and employment. More broadly, searchers tend to target people

[24] The same null result obtains if we replace log income with an inverse hyperbolic sine transformation of the reported income, or use as an outcome variable the presence of *any* self-employment income.

similar to them, but young, low-income people also non-trivially target older successful people and celebrities. The tax information of self-employed people is, ceteris paribus, significantly more likely to be targeted, and potential whistleblowing may be a motive for many of these searches. However, at least 90 percent of searches are highly unlikely to be driven by whistleblowing and tax compliance motivations, and a causal analysis of the effect of search on targets' income reporting finds small, statistically insignificant effects, even for self-employed targets. This evidence suggests that in equilibrium, compliance-motivated searching does not occur frequently, and searches themselves have minimal effects on compliance.

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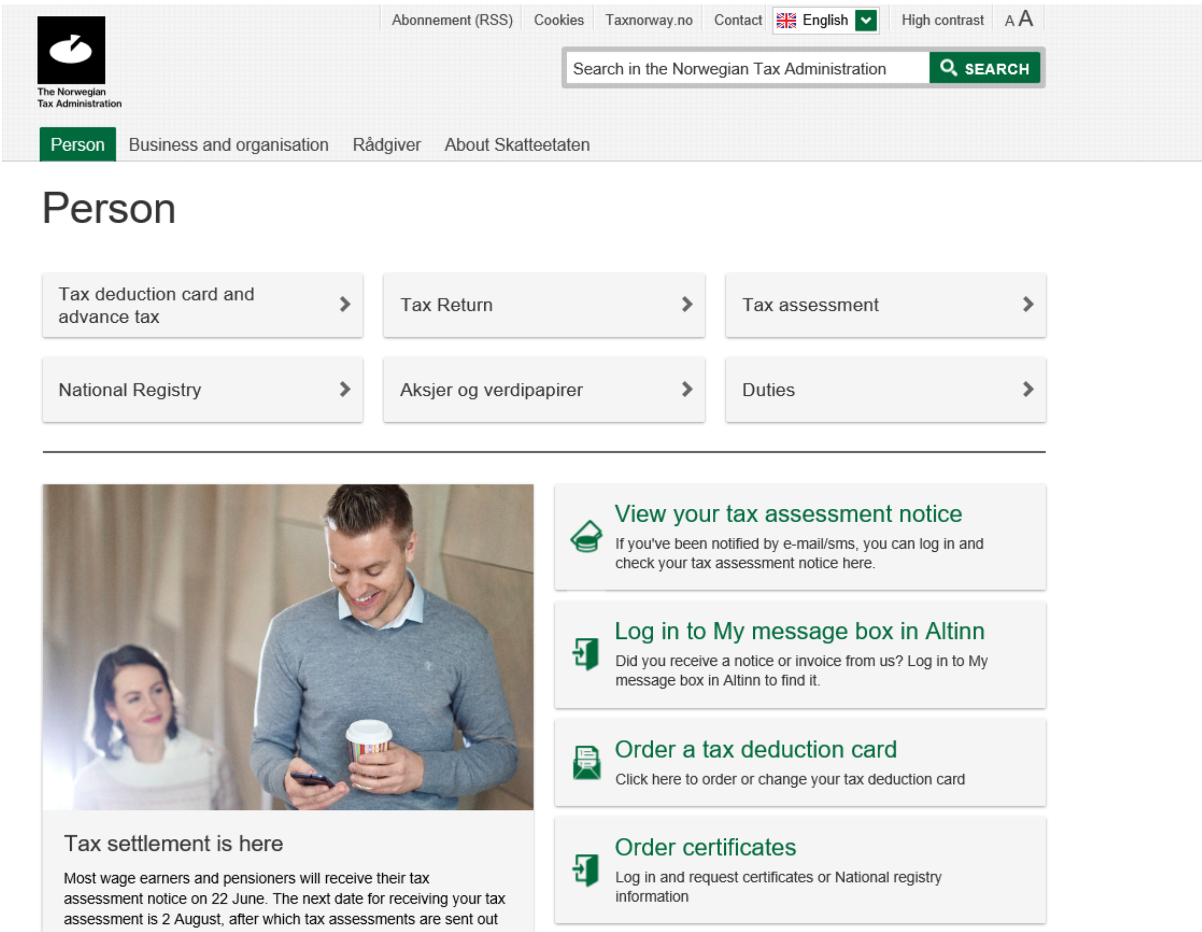
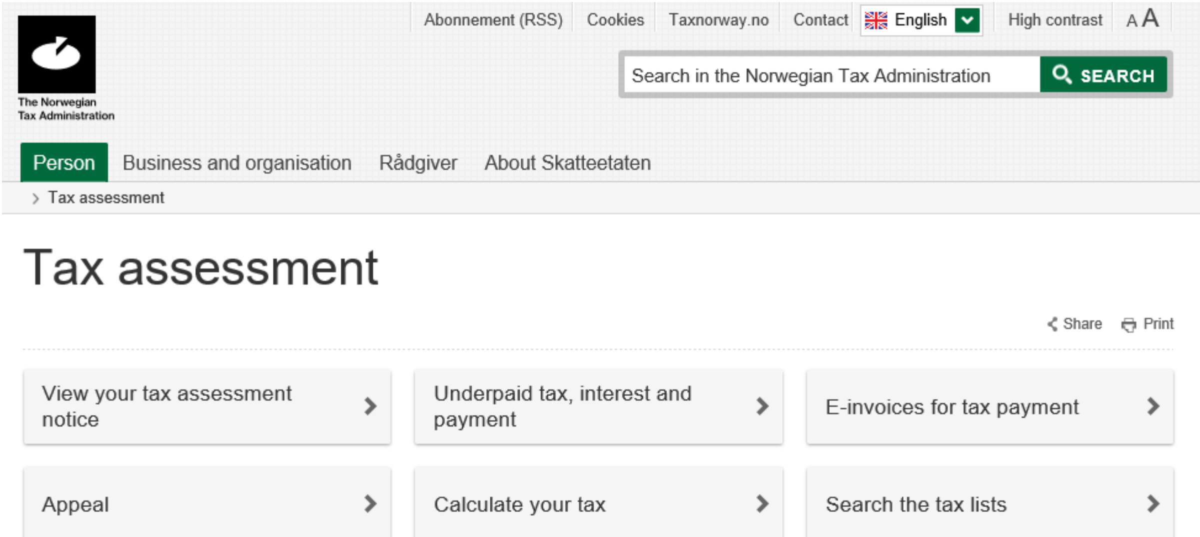
Appendix A. Screen Shot of Search Website

Screenshots Public tax information:

Accessed at www.skattetaten.no.

The first few screenshots show the website as one navigates to the place where one can search for others.




Abonnement (RSS)
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Contact
English
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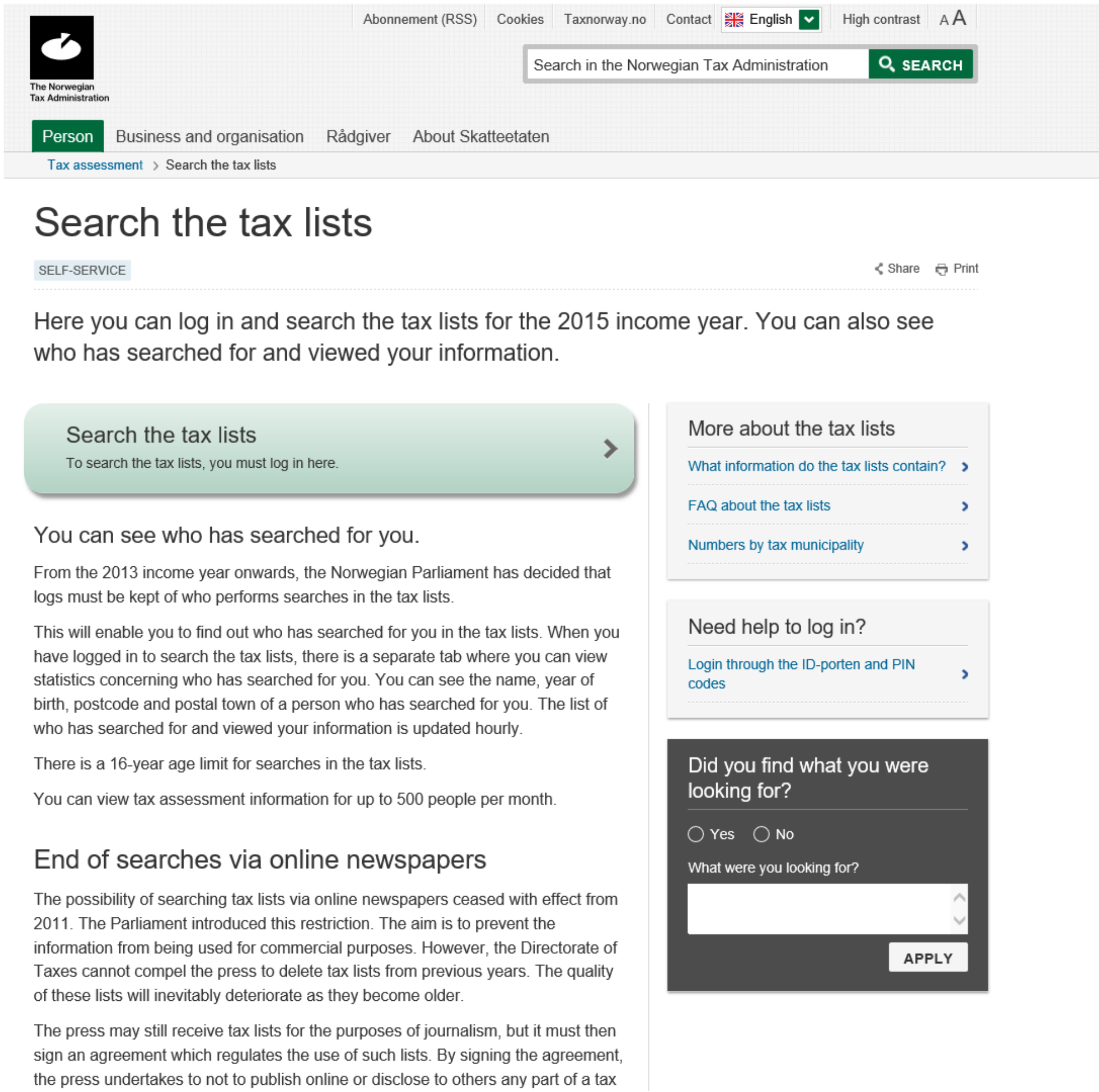
SEARCH
The Norwegian Tax Administration
Person
Business and organisation
Rådgiver
About Skatteetaten
Tax assessment
Tax assessment
Share
Print
View your tax assessment notice
Underpaid tax, interest and payment
E-invoices for tax payment
Appeal
Calculate your tax
Search the tax lists



Abonnement (RSS) | Cookies | Taxnorway.no | Contact | English | High contrast | A A

The Norwegian Tax Administration

Search in the Norwegian Tax Administration SEARCH

Person | Business and organisation | Rådgiver | About Skatteetaten

Tax assessment > Search the tax lists

Search the tax lists

SELF-SERVICE

Share Print

Here you can log in and search the tax lists for the 2015 income year. You can also see who has searched for and viewed your information.

Search the tax lists
To search the tax lists, you must log in here.

You can see who has searched for you.

From the 2013 income year onwards, the Norwegian Parliament has decided that logs must be kept of who performs searches in the tax lists.

This will enable you to find out who has searched for you in the tax lists. When you have logged in to search the tax lists, there is a separate tab where you can view statistics concerning who has searched for you. You can see the name, year of birth, postcode and postal town of a person who has searched for you. The list of who has searched for and viewed your information is updated hourly.

There is a 16-year age limit for searches in the tax lists.

You can view tax assessment information for up to 500 people per month.

End of searches via online newspapers

The possibility of searching tax lists via online newspapers ceased with effect from 2011. The Parliament introduced this restriction. The aim is to prevent the information from being used for commercial purposes. However, the Directorate of Taxes cannot compel the press to delete tax lists from previous years. The quality of these lists will inevitably deteriorate as they become older.

The press may still receive tax lists for the purposes of journalism, but it must then sign an agreement which regulates the use of such lists. By signing the agreement, the press undertakes to not to publish online or disclose to others any part of a tax

More about the tax lists

- What information do the tax lists contain?
- FAQ about the tax lists
- Numbers by tax municipality

Need help to log in?

- Login through the ID-porten and PIN codes

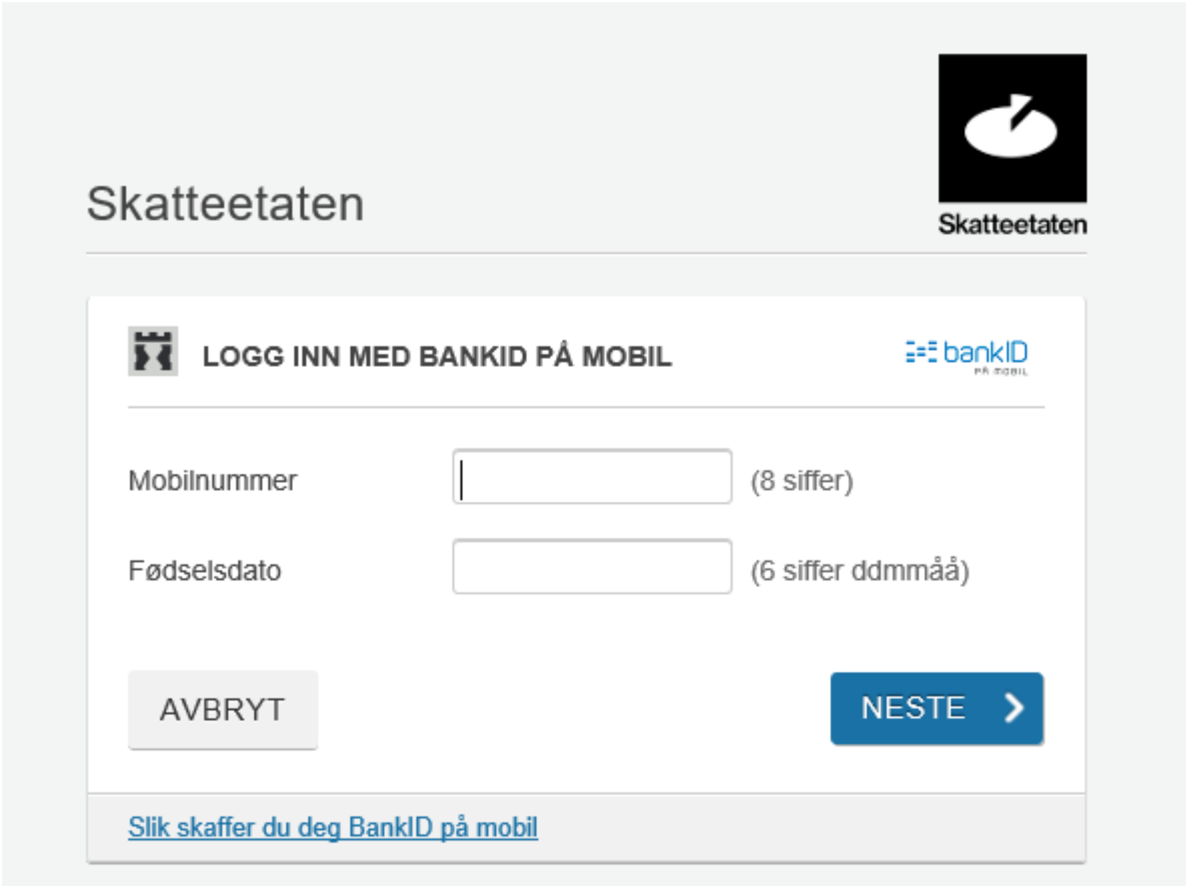
Did you find what you were looking for?

Yes No

What were you looking for?

APPLY

The above are English versions of web pages that are also available to taxpayers in Norwegian. After this page, there is no option of an English translation. From this point, one logs in by entering one's phone number and date of birth, and verifying one's identity via a SMS message sent to one's phone, which is registered with the government. There are also other ways to log in, but this method is the simplest one for most people.



Here, after logging in, one can enter the name of the person he or she wishes to search for. One must enter at least first+last name or last name+year of birth (need to click on "advanced search") in order to get any search results.

When clicking on *søkestatistikk* (search statistics), one can see who searched for you:

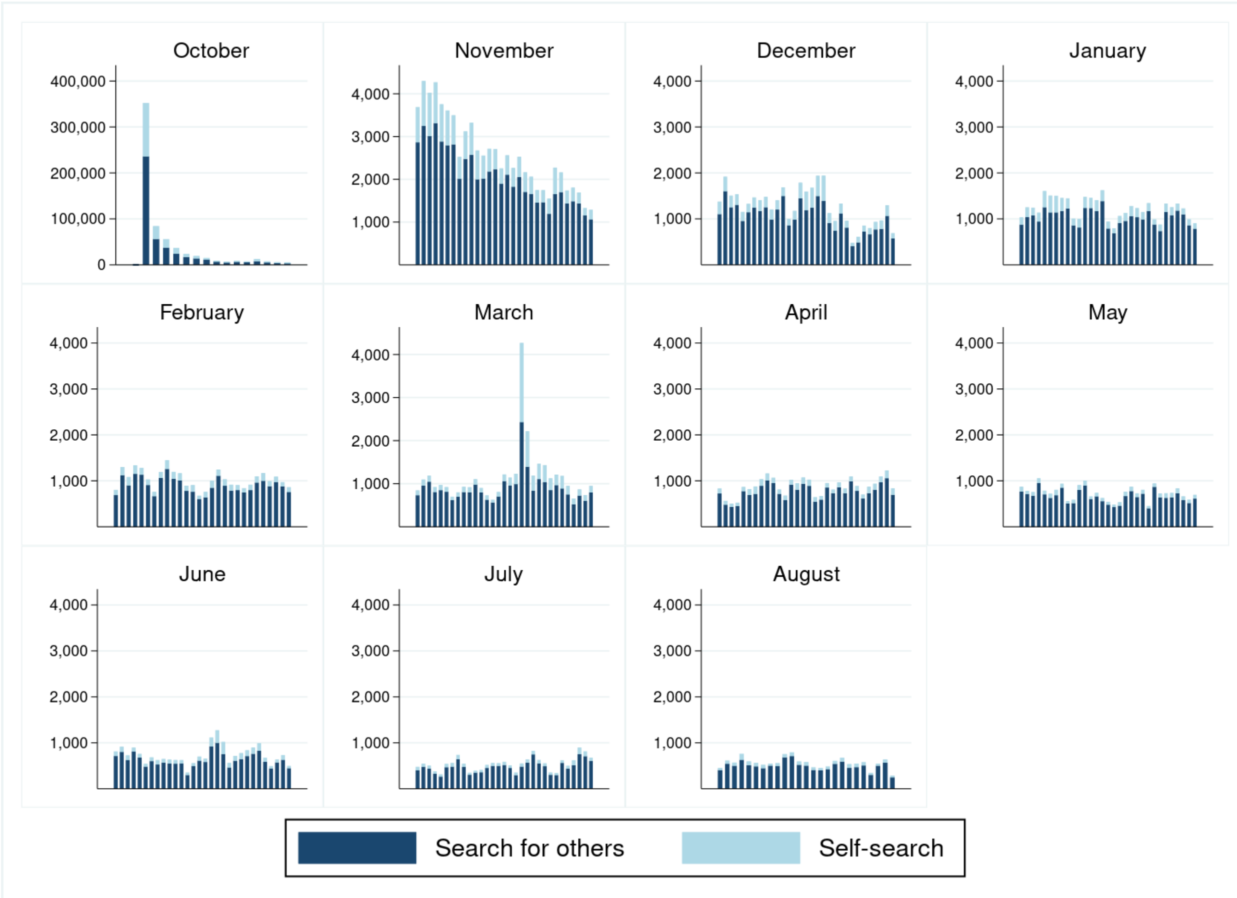
Appendix B. Who searches, and for whom do they search?

Table B.1: Searches by Month, 2014-2015

	Observations	Percent of Total
October	648,288	66.9
November	77,910	8.0
December	39,558	4.0
January	37,962	3.9
February	28,851	3.0
March	35,256	3.6
April	26,318	2.7
May	22,873	2.4
June	21,949	2.3
July	16,813	1.7
August	14,026	1.5

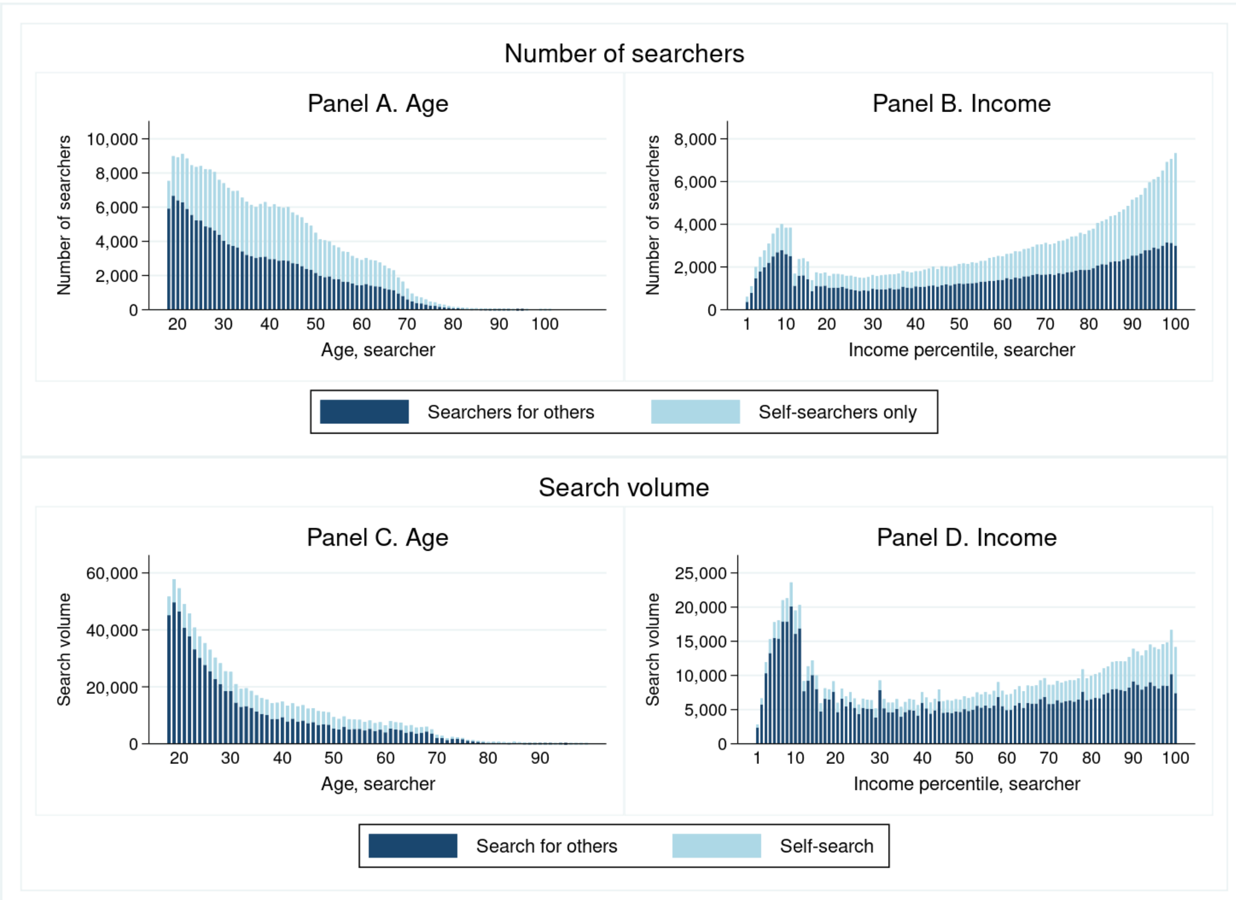
Notes: All searches in our sample, by the month the search was conducted.

Figure B.1: Daily Number of Searches by Month



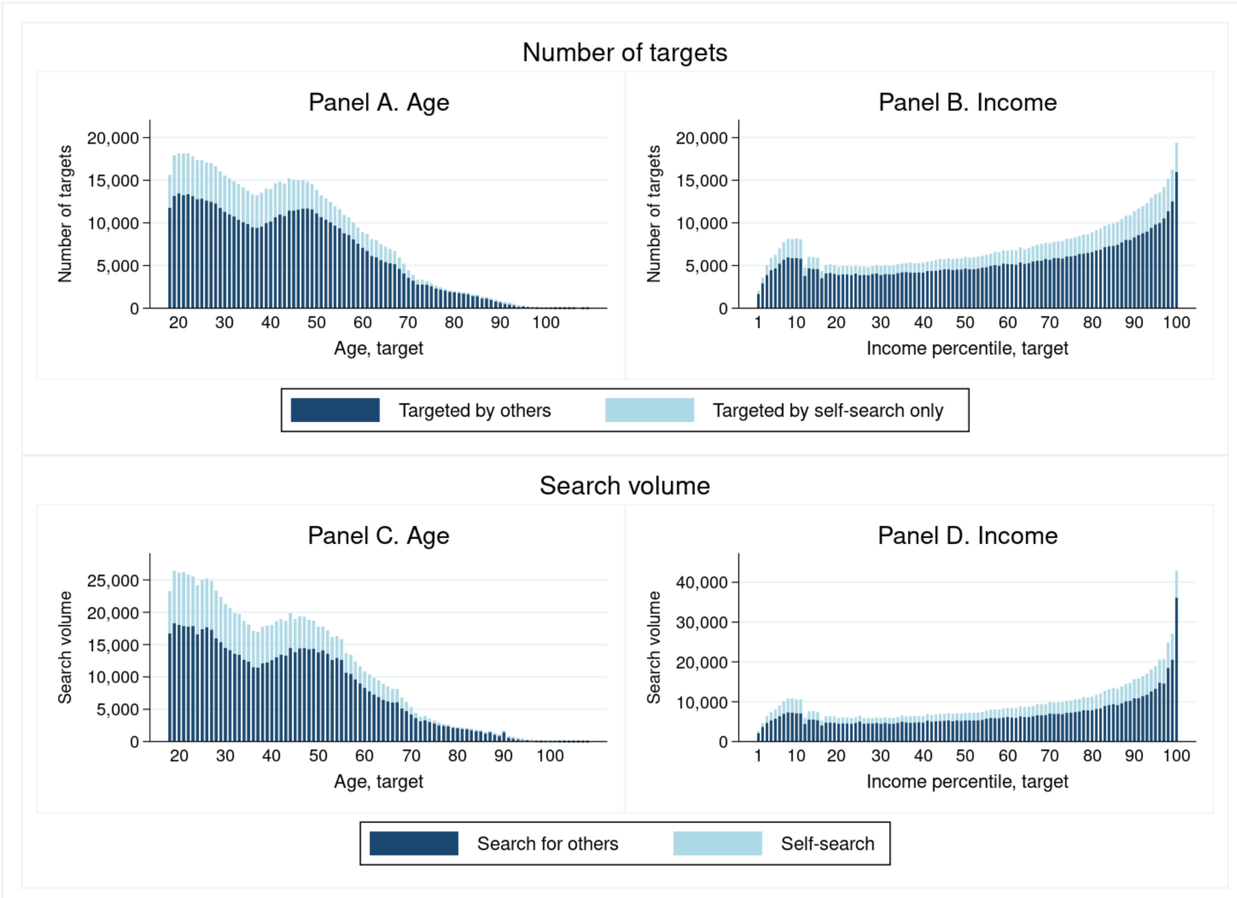
Notes: All searches in our sample, by the month and the day the search was conducted. Searches are categorized into self-search and search for others.

Figure B.2: Number of Searchers and Search Volume by Searcher's Age and Income



Notes: Panel A and B depict the number of distinct individual searchers by the age and the income percentile of the searcher, respectively. Panel C and D depicts the number of searches by the age and the income percentile of the searcher, respectively.

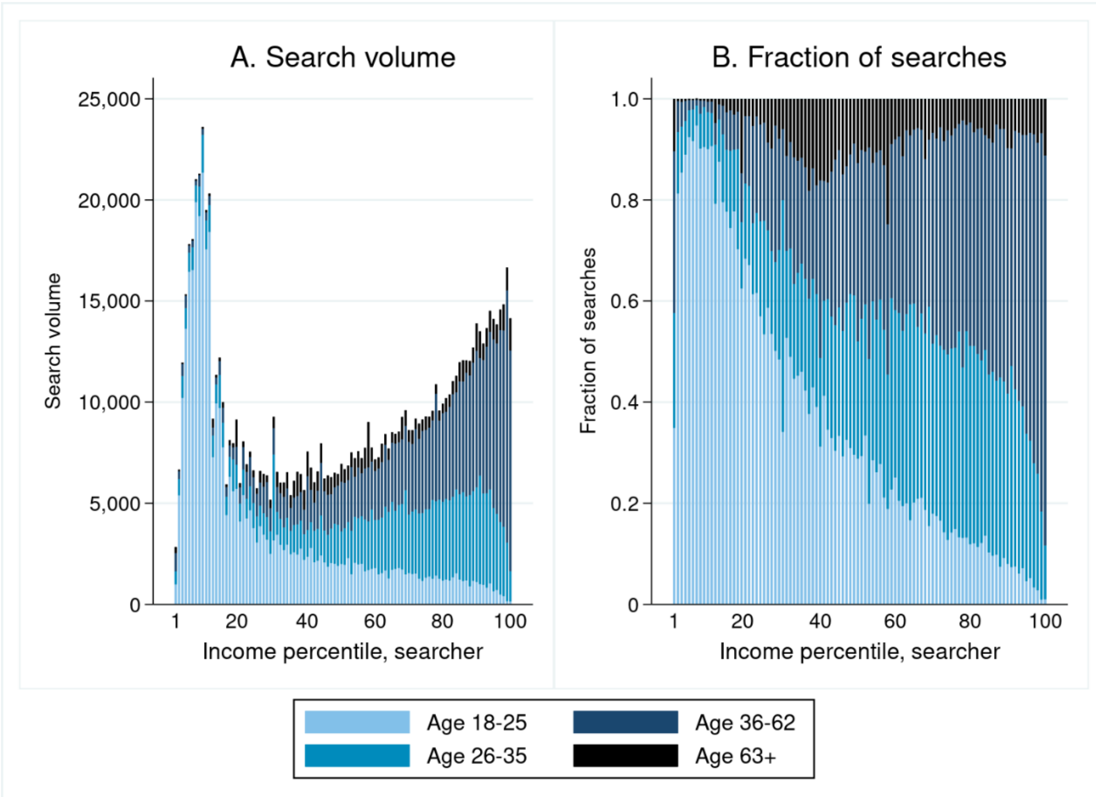
Figure B.3: Number of Targets and Search Volume by Targets' Age and Income



Notes: Panel A and B depicts the number of distinct targets (counting individuals) by the age and the income percentile of the target, respectively. Panel C and D depicts the number of searches by the age and the income percentile of the target, respectively.

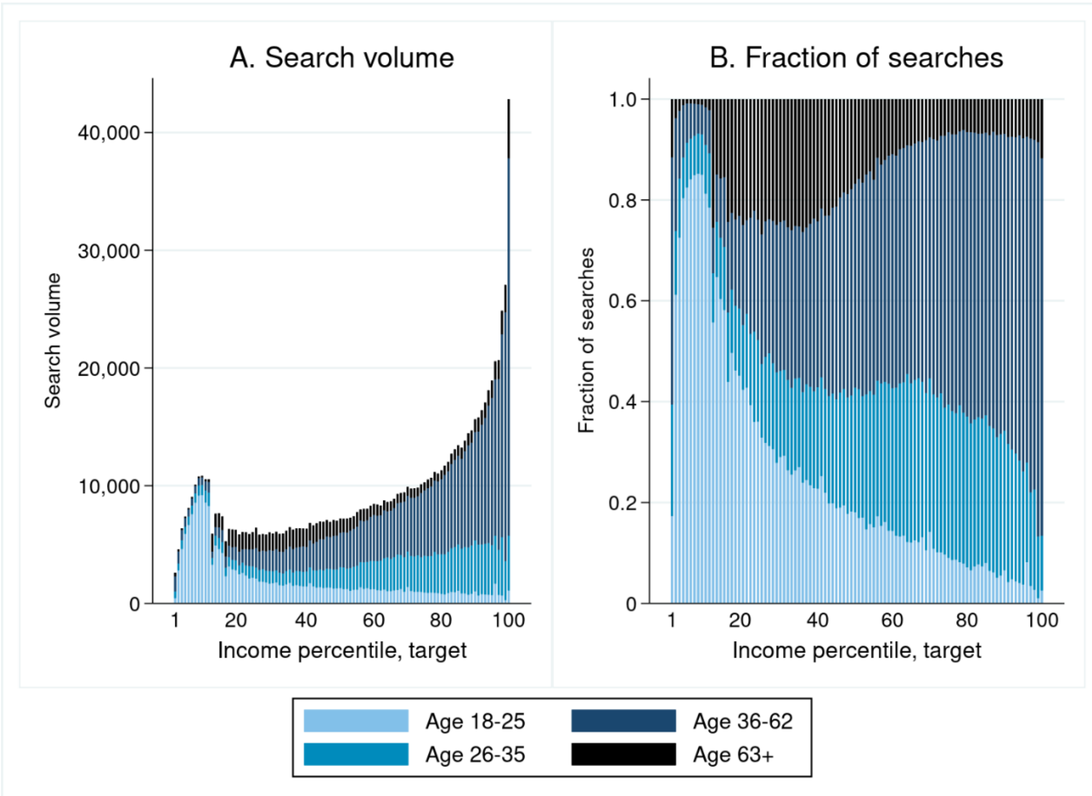
Figure B.3 illustrates the distribution of targets and volume of search by targets' income and age, and shows patterns that are broadly similar to those of searchers shown in Figure B.2, but with some noteworthy differences. Middle-aged taxpayers are more likely to be targets compared to being searchers, as are very high-income people. The bump in targets for very low-income people is present, but is not nearly as substantial compared to searchers. Above this small bump, the distribution of target income exhibits a relatively steep positive gradient. This indicates that both young, low-income searchers and middle-aged, high-income searchers search for high-income targets.

Figure B.4: Searcher's Age Distribution of Search Volume by Searcher's Income Percentile



Notes: The panels present a decomposition of search volume (Panel A) and the fraction of search volume (Panel B), respectively, in four age categories of the searcher by the income percentile of the searcher.

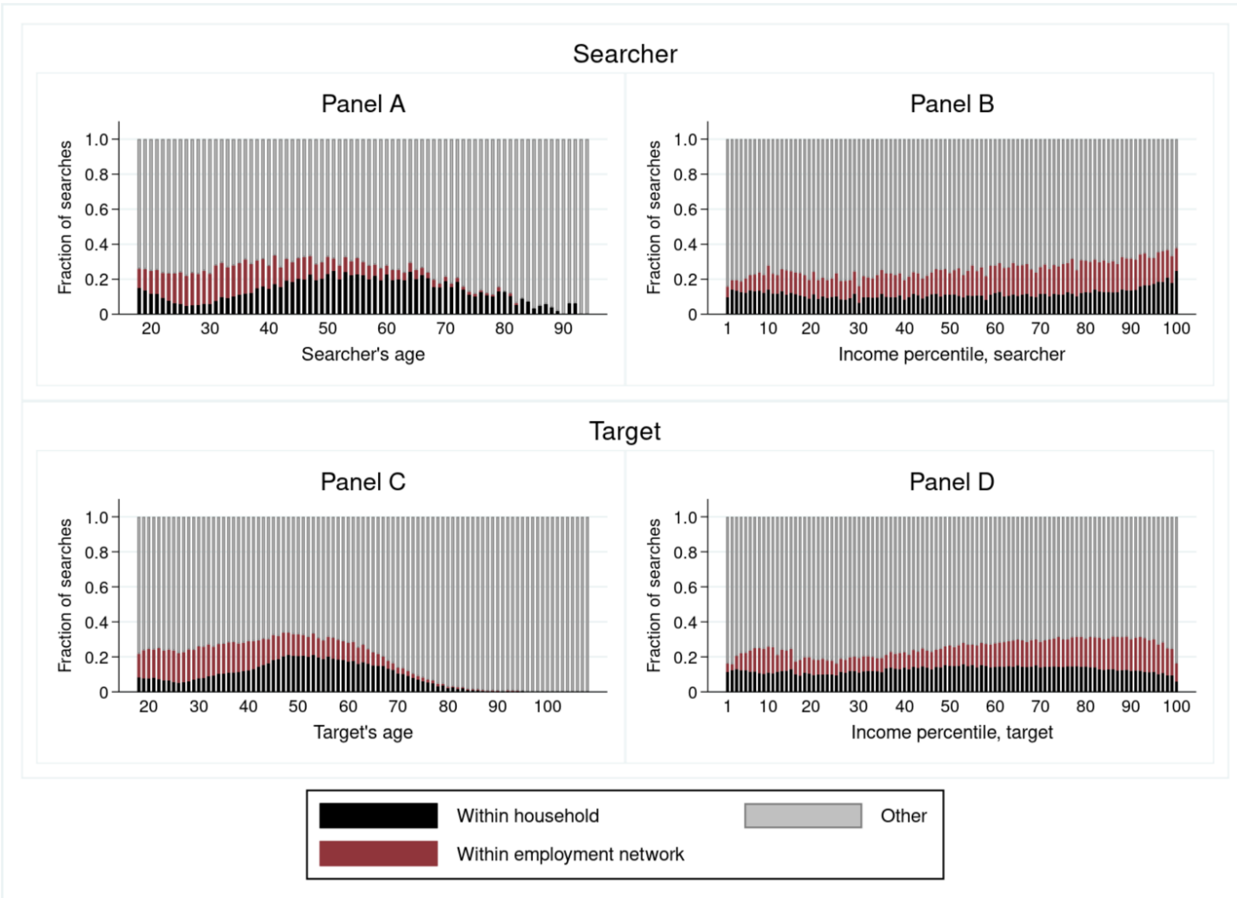
Figure B.5: Target's Age Distribution of Search Volume by Target's Income Percentile



Notes: The panels present a decomposition of search volume (Panel A) and the fraction of search volume (Panel B), respectively, in four age categories of the target by the income percentile of the target.

Appendix C. Who searches for whom?

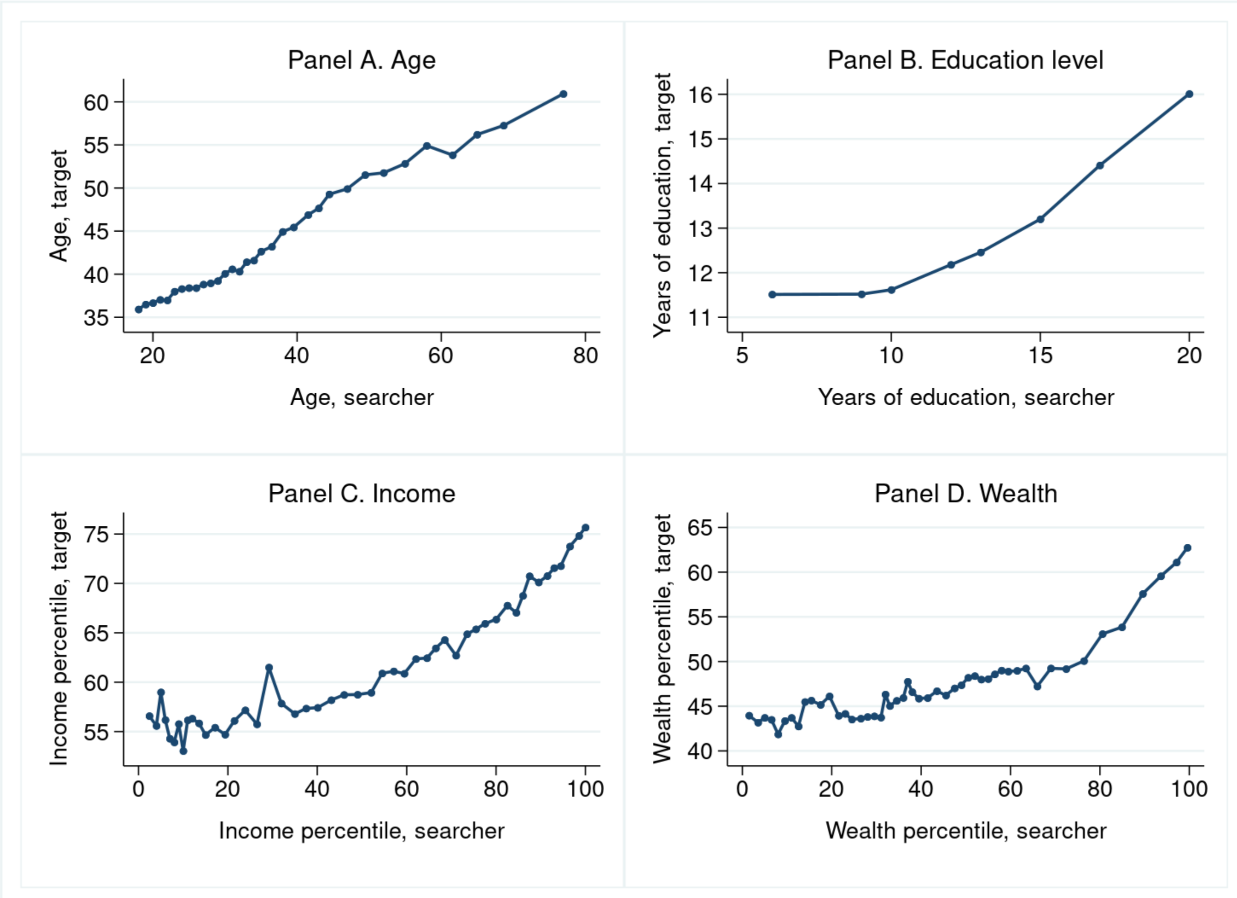
Figure C.1: Composition of Searches by Social Networks of Households and Employment. Fraction of searches.



Notes: The panels present the fraction of searches that occur within household, and within the same employment network. The network of households consists of persons residing in the same dwelling and related to each other as spouse, registered partner, cohabitant, and/or parent and child (regardless of the child's age). Information about the employment network is established based on information about all employers for each individual in 2013 and 2014. If any of the employers are the same for the searcher and the target, it is regarded as a search within an employment network. Panel A and B depicts the fraction of searches by the age and the income percentile of the searcher, respectively. Panel C and D depicts the fraction of searches by the age and the income percentile of the target, respectively.

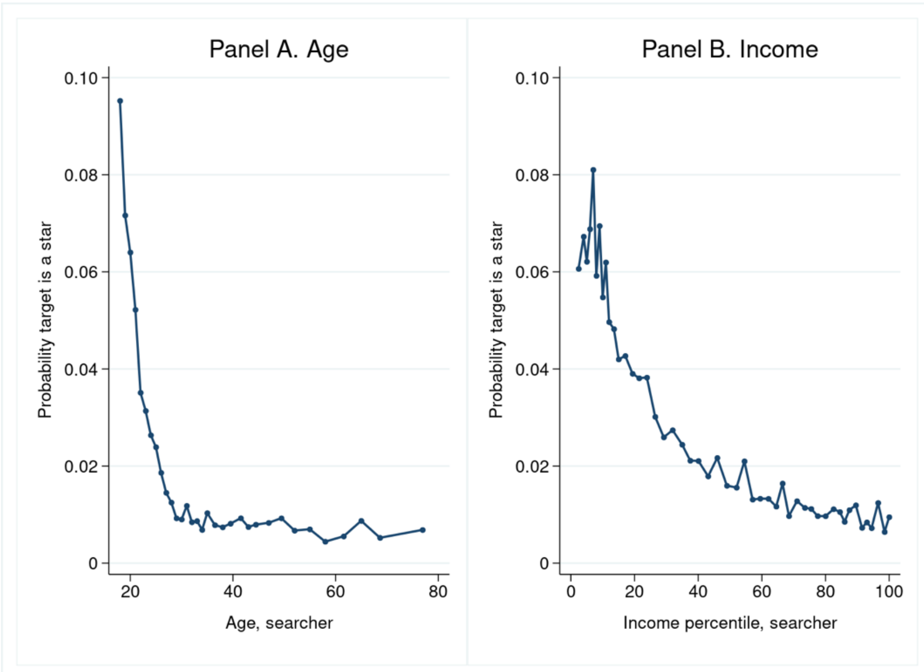
Figure C.2 provides more information about homophily by age, education level, income, and wealth, plotting the average characteristic of the target for bins of the searcher characteristic. In each case, a clear positive relationship emerges.

Figure C.2: Homophily in Search by Age, Education Level, Income and Wealth



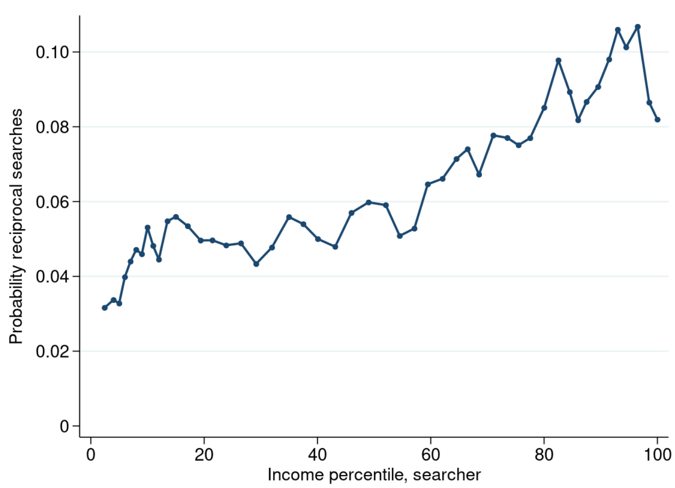
Notes: This figure presents binned scatterplots of the mean characteristics of a target characteristic, by the same characteristic of the searcher. We exclude self-searches and searches within household. Panel A through Panel D present results for age, education level, income and wealth, respectively. Years of education is computed by the highest registered education level of the individual. Income percentile refers to the income percentile among the overall adult population. Wealth percentile refers to the net wealth percentile among the overall adult population.

Figure C.3: Probability of Searching for a "Star," by Searcher's Age and by Searcher's Income



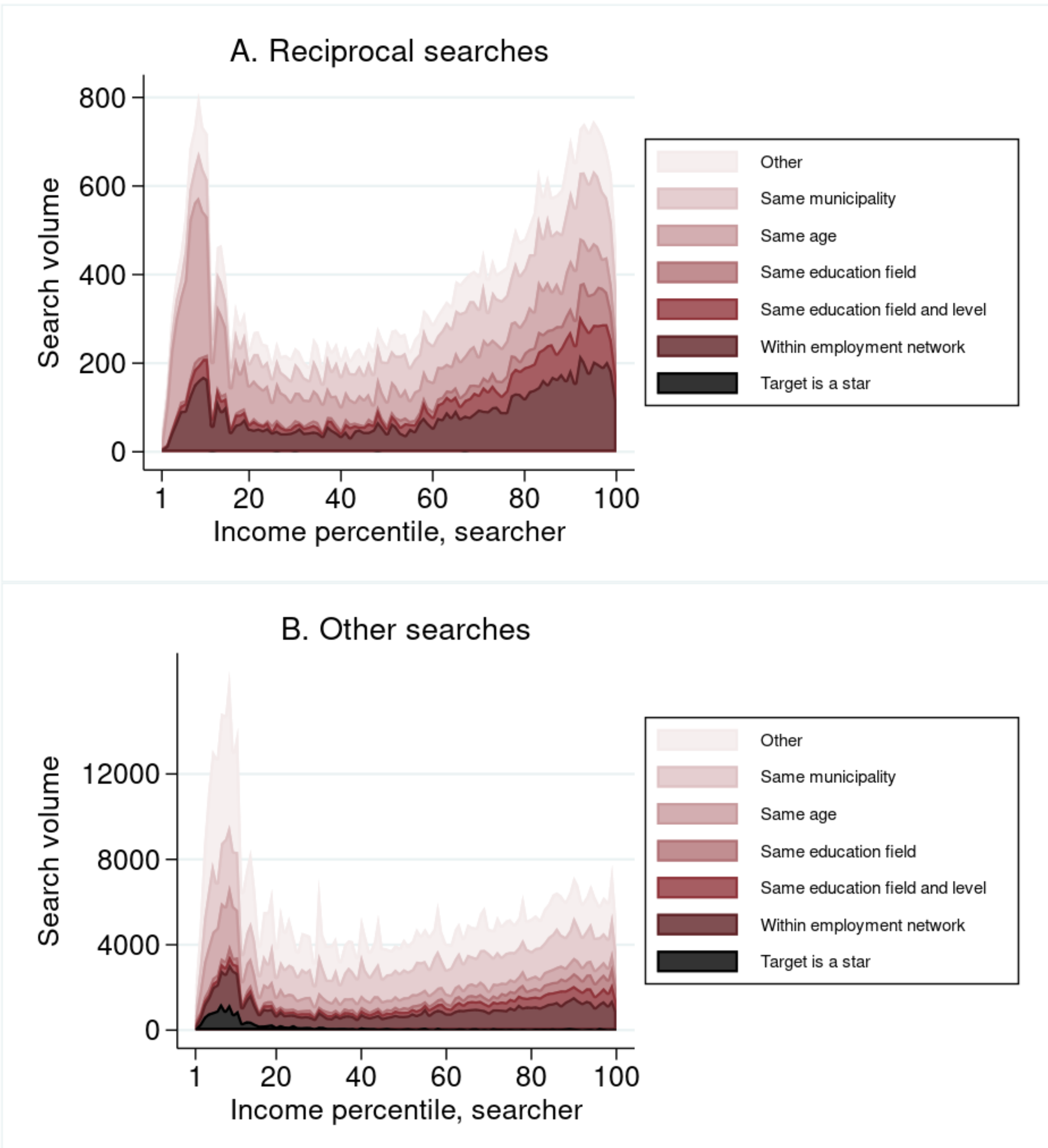
Notes: Panel A and Panel B present a binned scatterplot of the probability that the target is a star by the age and the income percentile of the searcher, respectively. We define a star as an individual targeted by at least 50 searchers (distinct individuals). The income percentile of the searcher in Panel B refers to the income percentile in the overall adult population.

Figure C.4: Probability of Reciprocal Searches by Searcher's Income



Notes: This figure presents binned scatterplot of the probability a search is reciprocated by searcher's income percentile. By definition, a reciprocal search occurs when we observe that the target of a given search also searched for the searcher.

Figure C.5: Composition of Searches by Searcher's Income. Reciprocal Searches and other Searches.



Notes: Panel A and Panel B of this figure decompose searches by the income percentile of the searcher, for reciprocal searches and other, non-reciprocated searches, respectively. By definition, a reciprocal search occurs when we observe that the target of a given search also searched for the searcher. Searches (excluding within household searches) are divided into 7 categories in the following order: 1) Target is a star; 2) Within employment network; 3) Same education field and level; 4) Same education field; 5) Same age; 6) Same municipality; 7) Other. A search falling in more than one of these categories will be assigned to the first criterion listed in the Figure.

Appendix D. Tax Disclosure and Tax Compliance

A concern with the specification in Section 6.2 is that the timing of filing is endogenous. Indeed, being targeted could directly affect when one files. Taxpayers can file a return and then revise it several times before the filing deadline. The filing date we observe in such instances would be the last date the individual revises their return. An individual could file before they were targeted, see that they were targeted, and then file again (perhaps because of being targeted and wishing to report more truthfully). Such an individual would be classified as "targeted after filing" in Table 4 when, in reality, they first filed before they were targeted and did respond to the policy, which could introduce selection bias into our estimates.

We address this concern with an instrumental variables design leveraging the fact that searches after the filing deadline could not affect the timing of filing. We therefore use whether the search occurred before the filing deadline as an instrument for whether the search occurred before the individual filed. For regular wage earners and pensioners, the filing deadline was April 30th, while the filing deadline for self-employed people was May 31st. Columns (3) and (4) of Table D.1 implement the reduced form of this design, replacing "targeted before filing" with "targeted before deadline" as the main treatment variable. We find very similar results, suggestive of little to no effect of search on reported income. More details about the IV procedure, including the first-stage results, are in the appendix.

Table D.1: IV Analyses of the Effect of Being Targeted on Reported Income

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS		First stage		IV	
Dependent variable	log taxable income 2014- log taxable income 2013		Searched before filing		log taxable income 2014- log taxable income 2013	
	All	Self-employed	All	Self-employed	All	Self-employed
Searched before filing	0.0019	0.0135			-0.0001	0.0168
	(0.0075)	(0.0172)			(0.0083)	(0.0312)
Searched before deadline			0.9257	0.6532		
			(0.0016)	(0.0106)		
Number of observations	57,111	6,135	56,929	5,305	54,695	5,014
R-squared	0.0000	0.0000	0.8485	0.4160	.	.
F-statistic			>99,999	3778.3		

Notes: Columns (1) and (2) report OLS estimates of the effect of being searched for before filing on reported taxable income in 2014, using the first difference in log taxable income between 2014 and 2013. Note that the individual fixed effects included in the specification from Table 5 are accounted for by using such a difference specification, in these columns and in columns (5) and (6). These results include all individuals targeted for the first time within the time window of +/- 60 days around the filing date. Columns (3) and (4) present the first stage of a 2SLS regression, where searched before filing is the endogenous variable and searched before the deadline is the exogenous variable. Columns (5) and (6) present the results of the second stage of a 2SLS regression, where the predicted value of searched before filing from columns (3) or (4) is used to estimate the causal effect of being targeted on reported income growth from 2013 to 2014. Searched before the filing/deadline are indicator variables of 0 (targeted after filing) or 1 (targeted before filing). Even-numbered columns restrict the sample to self-employed individuals, defined as individuals with non-zero (positive or negative) income from self-employment in year 2013.