

The Effects of Income Transparency on Well-Being

Evidence from a Natural Experiment*

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Abstract

In 2001, Norwegian tax records became easily accessible online, allowing individuals to observe the incomes of others. Because of self-image and social-image concerns, higher income transparency can increase the differences in well-being between rich and poor. We test this hypothesis using survey data from 1985–2013. We identify the causal effect of income transparency on subjective well-being by using differences-in-differences, triple-differences, and event-study analyses. We find that higher income transparency increased the happiness gap between rich and poor by 29% and the life satisfaction gap by 21%. Additionally, higher income transparency corrected misperceptions about the income distribution and changed preferences for redistribution. Last, we use the estimates for back-of-the-envelope calculations of the value of self-image and social-image.

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1 Introduction

What are the effects of income transparency on well-being? Higher income transparency may seem beneficial, because individuals can make informed choices. However, if individuals are prone to income comparisons, then income transparency can have large unintended effects on well-being, possibly benefiting the rich and hurting the poor. In this paper, we exploit a natural experiment in Norway to provide unique evidence about the effects of income transparency on well-being. Additionally, we use these estimates to provide back-of-the-envelope calculations of the value of self-image and social-image.

Tax records have been publicly available in Norway since the middle of the nineteenth century. However, these records were not easily accessible until 2001, when Norwegian newspapers created websites that allowed individuals to easily and effortlessly search tax records. These websites made it easy for individuals to observe the incomes of their social contacts. We provide evidence that, during the subsequent 12 years, these online search tools became widely and actively used. For instance, during the most active days, Norwegians were more likely to search each other's incomes than to search videos on YouTube.

The model from Appendix C shows that, due to self-image and social-image concerns, higher income transparency can increase the well-being gap between the rich and the poor.¹ On the one hand, higher income transparency can reduce the utility of a poor individual. Such individual would learn that she is poorer than she thought, and that knowledge would reduce her self-image utility; and her social contacts would learn that she is poorer than they thought, reducing her social-image utility. On the other hand, higher income transparency can increase the utility of a rich individual. This individual would learn that she is richer than she thought, increasing her self-image utility; and her social contacts would learn that she is richer than they thought, increasing her social-image utility.

To test this hypothesis, we measure the effect of the 2001 increase in transparency on the gradient between subjective well-being and income. We use survey data from 1985–2013 that includes two measures of subjective well-being, happiness and life satisfaction, which are widely used in the literature. We interpret these measures as proxies for experienced utility (Kahneman, Wakker, and Sarin, 1997). These same subjective measures have been validated in two ways. First, they are positively correlated with objective measures of experienced utility, such as emotional expressions, brain activity, and aggregate suicide rates (Sandvik et al., 1993; Urry et al., 2004; Di Tella, MacCulloch, and Oswald, 2003). Second, despite significant deviations, these same subjective measures are strongly correlated with decision utility (Benjamin, Heffetz, Kimball, and Rees-Jones, 2012, 2014; Perez-Truglia, 2015), suggesting

¹Self-image and social-image concerns have been used in a number of economic models: see for example Rabin (1994) and Bénabou and Tirole (2006), respectively.

that they measure something more meaningful than just mood.

Consistent with the hypothesis of income comparisons, we show evidence that higher income transparency caused an increase of 29% in the happiness-income gradient (p-value<0.01). In an event-study fashion, we show that the happiness-income gradient was constant in all the years before the disclosure change, then it increased sharply around 2001, and it persisted at the higher level during the 12 years of higher income transparency. In a triple-differences fashion, we note that individuals with higher Internet access should be more likely to be aware of and to use the online search tools. We show that the effects of the online publication of tax records were significantly higher for individuals with higher Internet access. Additionally, we show that the effects were close to zero and precisely estimated when we reproduced the analysis in Germany, a placebo country that was not affected by the change in disclosure. Last, we show effects on life satisfaction that are similar to and statistically indistinguishable from the effects on happiness: higher transparency increased the life satisfaction-income gradient by 21% (p-value<0.05).

The self-image mechanism predicts that income transparency affects well-being because of its effect on self-perceived income rank. We test this prediction using a survey measure of self-perceptions. We show that the change in disclosure corrected misperceptions about own relative income in a manner that is consistent with the self-image mechanism. Furthermore, we show that these changes in self-perceived income rank translated into meaningful changes in preferences for redistribution. On the one hand, the effect on self-perceptions suggests that the self-image mechanism explains at least some of the effects of transparency on well-being. On the other hand, the effects on self-perceptions cannot fully explain the magnitude of the effects on well-being, thus suggesting that other factors, such as social-image, also must play a role.

The finding that higher income transparency increased the well-being gap between rich and poor is consistent with anecdotal evidence. For example, media accounts reported that the online tax records were used to shame low-wage workers and to bully children from low-income households.² This finding also implies that poor individuals should be more likely to oppose the disclosure policy than rich individuals. Consistent with this prediction, results from a survey collected in 2007 by the research group Synovate indicate that a significant share of individuals (46%) were against the income transparency policy and that the poor were more likely to oppose it than the rich.³

Self-image and social-image are interesting beyond their implications for income transparency, because of their relevance for understanding human behavior and because of their

²See for example: “Norway Divided by Citizen Wealth Tables,” New York Times, October 23, 2009.

³Source: “Særnorsk praksis rundt skattelistene,” Aftenposten, October 12, 2011.

implications for taxation and other policies.⁴ However, despite the importance of this question, there is still no consensus about the economic significance of income comparisons. We use our estimates to provide a back-of-the-envelope estimation of the value of self-image and social-image. Under the assumption that the effects of transparency on well-being were caused by income comparisons, we show that the implied value of self-image and social-image must be economically significant. For instance, as a conservative lower bound, we find that, under the period of higher income transparency, self-image and social-image accounted for at least 22% of the happiness that individuals derived from their incomes.

This paper is related to various strands of literature. Most important, it relates to a literature on the effect of relative income on well-being.⁵ For instance, some studies show that, holding own income constant, subjective well-being decreases with the mean income in a reference group, such as the area of residence (Luttmer, 2004; Ferrer-i-Carbonell, 2005).⁶ However, there are important caveats with this evidence. First, some studies find no effects and even effects in the opposite direction.⁷ Second, the estimates are subject to plausible omitted-variable biases. Most notably, basic economic theory predicts that, even without relative concerns, a given income should buy less happiness in areas with higher average income (Balassa, 1964; Samuelson, 1964). We contribute to this literature by presenting novel evidence about the value of income comparisons using an entirely different identification strategy.

This paper is also related to a study by Bø, Slemrod, and Thoresen (2015) of the effect of disclosure of tax records on tax evasion in Norway. Intuitively, disclosing tax records may deter tax evasion by encouraging others with relevant information about true tax liability to come forward and by threatening evaders with social sanctions (see also Perez-Truglia and Troiano, 2015). Bø, Slemrod, and Thoresen (2015) find that the change in income disclosure increased reported income among business owners by 2.7%, which is approximately 0.2% of

⁴For example, self-image and social-image concerns can create positional externalities that reduce social welfare and could be corrected with taxes. For a theoretical discussion, see for example Boskin and Sheshinski (1978) and Frank (1985).

⁵This literature began with the Easterlin Paradox: i.e., the claim that income and self-reported happiness are positively correlated across individuals within a country but that average happiness within countries does not seem to rise over time as countries get richer (Easterlin, 1974). Despite the importance of this question for the discipline, however, economists seem to be largely divided regarding the theory of and supporting evidence for the Easterlin Paradox (e.g., Hagerty and Veenhoven, 2003; Stevenson and Wolfers, 2008).

⁶Some studies use a slightly different specification: holding absolute income constant, well-being increases with the position in the distribution of income of the reference group. For an extensive review of the literature, see Clark, Frijters and Shields (2008).

⁷Senik (2004) finds that mean income in the reference group actually increases happiness. Clark, Kristensen and Westergård-Nielsen (2009) find that life satisfaction increases with mean neighborhood income, although they also find that – holding both own income and mean neighborhood income constant – satisfaction increases with neighborhood income rank. And Deaton and Stone (2014) find no evidence of income comparisons with life satisfaction data.

the 2001 income tax revenue in Norway. This evidence confirms that the change in disclosure produced an effect that supporters of open disclosure had predicted. We study an unintended effect, as highlighted by some detractors of open disclosure: the higher tax transparency generated a large redistribution of well-being from the poor to the rich, presumably because of income comparisons. This unintended effect should be considered when deciding how to disclose sensitive information, such as tax records, not only in Norway but around the world.

Our paper is also related to the study by Card, Mas, Moretti and Saez (2012) of the effects of income transparency on job satisfaction. They sent emails to a random sample of university employees with information on how to access a website that listed the wages of all university employees. In a follow-up survey, they found that, for workers with below-median salaries within their occupation, the informational treatment decreased their satisfaction with their wages and their jobs. Consistent with this finding, Rege and Solli (2015) show evidence that the disclosure of tax records in Norway increased the probability of quitting for workers with lower salaries within their occupation. If anything, their findings can be interpreted as suggestive evidence that poor individuals benefit from higher income transparency, because they can find out if they are being under-paid. On the contrary, our evidence suggests that higher income transparency benefited the rich and hurt the poor.

Last, our findings on the effects of income transparency on self-perceived income rank confirm evidence from survey experiments that individuals misjudge their own income rank and that these errors can be corrected by educating individuals about the income distribution (Cruces, Perez-Truglia, and Tetaz, 2013; Karadja, Mollerstrom, and Seim, 2015).

The rest of the paper proceeds as follows. Section 2 describes relevant details about the disclosure policy. Section 3 presents the econometric specification and the survey data. Section 4 presents the results. Section 5 presents back-of-the-envelope estimates of the value of self-image and social-image. The last section concludes.

2 Relevant Institutional Details

2.1 Brief History of the Disclosure Policy

In this section, we summarize the main events in the history of the Norwegian disclosure policy that are relevant for the empirical analysis.

Even though tax records have been publicly available in Norway since the middle of the nineteenth century, they were not easily accessible before 2001. Individuals who wanted to learn about someone else's income had to visit the local tax office or city hall during a three-week period and search through a book with records for thousands of taxpayers from the

same area.⁸

In the fall of 2001, a Norwegian newspaper posted these tax records online for the first time, so that any Norwegian with Internet access could view the tax records of everyone in the country for free at any time. These records included the individual's full name, birth year, city, postal code, taxes, net income, and net worth. This site became one of the most popular websites in Norway, and soon other major newspapers created their own versions. These sites included a search tool to locate individuals by name, address and other criteria. For example, a user could search for her last name to find her relatives, or search for her postal code to find her neighbors. For reference, Appendix B provides snapshots of some of these websites, including a sample search result. The data published on these websites were indexed by all the popular search engines, including Google. As a consequence, searching for the name of a Norwegian citizen in Google would often display the individual's tax record in the top search results (Teknologiradet, 2010).

Between 2001 and 2013, the last year of our survey data, certain factors may have contributed to a slight increase or decrease in income visibility, but none of these changes in visibility was remotely comparable in size to the change in 2001.

A factor that may have contributed to higher income transparency is the increase in Internet access. According to Statistics Norway, the share of households with Internet access at home increased from 60% in 2003 to 93% in 2013. This increase may have translated into more traffic to the websites listing the tax records and thus higher income visibility. Also, the newspapers gradually introduced more convenient and sophisticated ways of browsing tax records. In 2009, for example, one newspaper released a smartphone application that connected to Facebook to automatically create leaderboards with the highest and lowest earners among Facebook friends. This application also allowed users to browse maps displaying the incomes of each neighbor. This quickly became one of the most downloaded applications in the country (Teknologiradet, 2010).

A factor that may have contributed to lower income transparency is the change in government regulations. We provide here a brief summary of these changes – see Appendix B for a more detailed description. From 2004 to 2006, income searches were limited to the three-week period following the release of the data. Due to the timing of the survey, however, this temporary change is unlikely to affect our estimates significantly.⁹ In 2011, new restrictions required individuals to log in to the tax agency website to conduct searches. Although

⁸In selected municipalities and only for recent years, local organizations sold books with information from the local tax rolls. For more details about these books, see Bø, Slemrod and Thoresen (2015).

⁹First, our survey was collected every two years and thus covers only one year of this restricted period. Second, for that year of restricted access, a significant share of respondents probably completed the questionnaire during the three-week period of unrestricted access.

this restriction may have reduced the number of searches conducted per year, in the next subsection we show that the search volume was still substantial. Finally, in 2014 the searches became non-anonymous, but this last event is not directly relevant for the empirical analysis because it occurred one year after the last year of the survey data used in the empirical analysis.

2.2 Popularity of the Search Tool

According to Norway’s Ministry of Finance (2014), 920,896 users conducted slightly more than 17 million searches in 2013. Given that there were about 4 million adults in Norway, these statistics imply that one quarter of the adult population made at least one search in the tax records that year and that the average user conducted 17 searches.¹⁰ Given that in 2013 users faced the extra hassle of logging to the tax agency website with a pin and a password, it is likely that the numbers of users and searches were significantly higher in previous years.

We also use data from Google Trends to measure the popularity of the income search tool. These data measure the number of times that a given keyword is searched for using the Google search engine.¹¹ Figure 1.a shows the popularity of selected keywords in 2010 (the last year when users were allowed to conduct searches outside of the official website of the tax agency). The first category, Skattelister, includes searches for the two words used most often to refer to the tax records: skattelister and skattelistene (their literal translation is “tax list”). For instance, the URL of one of the popular websites that offered access to the tax records was www.skattelister.no. As benchmarks, we use data on two keywords that are consistently among the most popular keywords around the world: “weather” and “YouTube.” As a proxy for the general interest in information about taxes, we study the number of searches for “tax” and “taxes.”

The left half of Figure 1.a shows the results for Norway. The search totals are normalized as a fraction of “YouTube” search totals. For every five “YouTube” searches, there was about one “skattelister” search, suggesting a remarkable interest in searching for information about the incomes of others.¹² Additionally, Norwegians were more likely to search for others’ incomes than they were to search “weather.” Searches for “skattelister” were roughly three times higher than those for “tax,” suggesting that the popularity of the search tool is not explained by a general interest in taxes. A final concern is that the interest in these benchmark keywords may be unusually high or low in Norway. The right half of Figure 1.a

¹⁰Under the conservative assumption that each search results in just 2 unique profile views, then each Norwegian adult would have been viewed by others an average of 9 times in 2013.

¹¹For a discussion of the advantages and limitations of these data, see Stephens-Davidowitz (2014).

¹²As additional benchmark, the number of searches for Youtube are slightly higher than the combined searches for “porn” and its Norwegian translation, “porno.”

provides comparable search data for Sweden, a country that is geographically adjacent to Norway and shares cultural and demographic characteristics. As expected, relative searches for “weather,” “tax,” and “YouTube” are roughly similar between Norway and Sweden.

Figure 1.b shows the weekly evolution of searches for the same keyword categories in Norway during 2010. The search volumes are normalized so that searches in all categories sum up to 1 in the first week of 2010. During most of the year, searches for “skattelister” were stable, at roughly twice the volume of searches for “tax” and at about the same level as for “weather.” In the third week of October, when data from the previous tax calendar year was released, searches for “skattelister” increased sharply. We find a consistent peak in visits to the search tool using the Internet browsing data described below. During the week of the release of tax data, the number of searches for “skattelister” exceeded the number of searches for “YouTube,” suggesting that Norwegians were more likely to search for the incomes of others than to search for videos on YouTube.

2.3 Uses of the Search Tool

The official statistics and Google data suggest that websites with tax records were very popular, but they do not provide any evidence about the users’ intentions. For example, rather than searching for the incomes of social contacts, the vast majority of visitors may have searched for the incomes of celebrities. To address this and other related concerns, we exploit unique data on browsing behavior by users visiting one of the websites that offered an income search tool. The data originate from a large panel of Internet users and thus includes a small but non-negligible fraction of all Internet users in Norway. Our sample includes more than 200,000 user sessions in 2010 that included at least one visit to this website to browse the tax records.

First, we study the possibility that individuals used these search tools to learn about the incomes of actors, politicians, and other celebrities. Indeed, Norwegian newspapers sometimes published articles about the incomes of celebrities using data from the tax records. To explore this hypothesis, Figure 2.a indicates the percentage of the total visits corresponding to profiles that have been visited only once, to profiles that have been visited twice, and so on. If the primary use for the search tool was to search for celebrities, then most traffic should be directed towards a small number of profiles (i.e., the celebrities) with hundreds or thousands of visits each. The data strongly reject this hypothesis. If we defined celebrity profiles as those visited at least 100 times in our sample, then visits to the profiles of celebrities would explain less than 3% of all the visits to the website.

Second, we study the possibility that a few professional users, such as marketing companies trying to build client lists, may account for the vast majority of searches. Ideally, we

would test this hypothesis by looking at the distribution of the number of searches across users. However, because the browsing data does not include user identifiers, we use session identifiers instead. Figure 2.b provides a histogram of the number of profiles visited per session during the day of the release of the 2009 tax calendar data.¹³ The search patterns suggest that the traffic cannot be explained by a minority of professional users. If we defined professional users as those visiting more than 100 profiles per session, then professional users would account for just 0.27% of the total visits to the website.

Third, we study the possibility that individuals used the search tool to search themselves, such as to verify information from their own tax reports. In this case, the histogram in Figure 2.b should indicate that the majority of users visited just one profile (i.e., their own profile). On the contrary, the data suggest that the typical session included visits to several profiles. Thus, even under the conservative assumption that all sessions with a single profile visit corresponded to individuals searching for themselves, those types of searches would comprise just 2.62% of the total visits to the website.

In summary, this evidence suggests that, consistent with the anecdotal evidence reported by the Norwegian media, a large fraction of the population used the search tool regularly and with the goal of learning about the incomes of social contacts.

3 Econometric Specification and Survey Data

3.1 Econometric Specification

The baseline specification is the following:

$$SWB_{i,t} = \alpha_1 \cdot IncomeRank_{i,t} + \alpha_2 \cdot IncomeRank_{i,t} \cdot I_t^{01-13} + X_{i,t}\beta + \delta_t + \epsilon_{i,t} \quad (1)$$

$SWB_{i,t}$ is a measure of subjective well-being of individual i in year t , with a higher value denoting higher well-being. Details about this and all the other variables used in the analysis are included in the following data section. $IncomeRank_{i,t}$ is the position of individual i in the national distribution of household income in year t , where 0 denotes the poorest household and 1 denotes the richest household. In any given year, $IncomeRank_{i,t}$ is a monotone transformation of absolute income, just like the logarithm of absolute income, for example. We let $IncomeRank_{i,t}$ enter linearly, because this linear specification fits the data well and, presumably for that reason, it is widely used in the literature (Ferrer-i-Carbonell, 2004).¹⁴ I_t^{01-13} is a dummy variable indicating the period of higher income transparency.

¹³This is a lower bound on the number of profiles visited per user that day, because one user may visit the website in multiple sessions and from multiple devices.

¹⁴In the subjective well-being literature, there is robust evidence of a linear relationship between subjective

It equals 1 if $t \in [2001, 2013]$ and 0 otherwise. $X_{i,t}$ is a vector with a typical set of control variables used in related studies (also listed in the following data section), δ_t denotes the year dummies, and $\epsilon_{i,t}$ denotes the error term.

The coefficient α_1 corresponds to the average gradient between $SWB_{i,t}$ and $IncomeRank_{i,t}$ from 1985 to 2000 and is expected to be positive. The coefficient α_2 measures the change in the happiness-income gradient from 1985–2000 to 2001–2013. Under the hypothesis of income comparisons, discussed in the model from Appendix C, we expect α_2 to be positive. That is, the happiness-income gradient is expected to increase over the entire period of higher income transparency. This regression has a differences-in-differences interpretation in which I_t^{01-13} corresponds to the indicator of post-treatment period and $IncomeRank_{i,t}$ corresponds to the intensity of treatment (from 0 to 1).

An important concern with this specification, as in every other differences-in-differences design, is the possibility of differential pre-trends. In other words, it is possible that the happiness-income gradient had been gradually increasing even before 2001, yielding $\alpha_2 > 0$, even if there was not a discontinuous change in this gradient around 2001. One traditional way of addressing this concern is to include group-specific linear trends:

$$SWB_{i,t} = \alpha_1 \cdot IncomeRank_{i,t} + \alpha_2 \cdot IncomeRank_{i,t} \cdot I_t^{01-13} + \gamma \cdot IncomeRank_{i,t} \cdot (t - 1985) + X_{i,t}\beta + \delta_t + \epsilon_{i,t} \quad (2)$$

In this specification, the coefficient α_1 corresponds to the happiness-income gradient in 1985. The coefficient γ corresponds to the linear trend for this gradient from 1985 to 2013. The coefficient α_2 corresponds to the change in the happiness-income gradient around 2001 in addition to the linear trend. If the happiness-income gradient changed sharply around 2001, then we would expect $\gamma = 0$ and $\alpha_2 > 0$.

Another traditional way to address the possibility of differential pre-trends is based on the following specification:

$$SWB_{i,t} = \alpha_1 \cdot IncomeRank_{i,t} + \alpha_2 \cdot IncomeRank_{i,t} \cdot I_t^{01-13} + \alpha_3 IncomeRank_{i,t} \cdot I_t^{97-00} + X_{i,t}\beta + \delta_t + \epsilon_{i,t} \quad (3)$$

I_t^{97-00} is a “fake” treatment indicator that occurs just before the actual change in disclosure: i.e., a dummy variable that equals 1 if $t \in [1997, 2000]$ and 0 otherwise (because the survey is biennial, this period includes observations for 1997 and 1999 only). In this specification, α_1 corresponds to the happiness-income gradient from 1985–1996, whereas α_2 measures

well-being measures (e.g., happiness, life satisfaction) and the logarithm of household income. Another well-established fact is that *Income Rank* is roughly proportional to the logarithm of income (Chetty, Hendren, Kline and Saez, 2014). As a result, it is not surprising that subjective well-being is linearly related to *Income Rank*.

the change in that gradient from 1985–1996 to 2001–2013, and α_3 measures the change in the happiness-income gradient from 1985–1996 to 1997–2000. If the happiness-income gradient changed sharply around 2001, we would expect $\alpha_2 > 0$ and $\alpha_3 = 0$. Furthermore, we conduct an event-study analysis that provides an even more granular view of the evolution of the happiness-income gradient in the years before and after the change in disclosure.

Even if we established that the change in the happiness-income gradient occurred exactly in 2001, this effect may not have been caused by the change in income disclosure, but instead by some other major change that took place in 2001. To the best of our knowledge, there was no other event around that time that could have had such a large effect on the happiness-income gradient. To address this concern more directly, we propose a triple-differences design. Individuals without Internet access may be unaware of the search tool and therefore less likely to use it to look at the incomes of others and less likely to feel observed by others through the search tool.¹⁵ Thus, we expect that the change in disclosure affected the well-being of individuals with higher Internet access but had a smaller effect, and possibly no effect, on individuals with lower Internet access.¹⁶

This triple-differences framework presents two challenges. The first challenge is conceptual: the share and composition of individuals with Internet access has changed dramatically over time. For instance, it would be impossible to estimate the change in the happiness-income gradient from 1985–1996 to 2001–2013 for individuals with high Internet access, because few people had Internet access before 1996. The second challenge is a data challenge: the survey question about Internet access was added in 1999, and with a single year of pre-treatment data the statistical power would be largely insufficient for a triple-differences analysis.

We propose the following method to address the conceptual and data challenges simultaneously. Instead of basing the third difference on whether individuals currently have low or high Internet access, we base the third difference on whether individuals, according to their current observable characteristics, would be predicted to have high or low Internet access after the Internet becomes available. Let $InternetRank_{i,t}$ be the position of individual i in the national distribution of predicted Internet access in 2001, according to the individual’s characteristics in year t and ranging from 0 (lowest access) to 1 (highest access). For instance, if being married and educated predicts high Internet access in 2001, then married and educated

¹⁵Also, it is possible that individuals with higher Internet access are more interested in social comparisons, as suggested by Clark and Senik (2010).

¹⁶Bø, Slemrod and Thoresen (2013) use an alternative triple-differences design: given that some municipalities offered the data in print catalogs before 2001, the effect of the change in disclosure of 2001 should be lower in those municipalities. However, we cannot use this identification strategy because they only collected data for a few municipalities and thus we would be restricted to a small number of survey responses.

people are assigned a high value for $InternetRank_{i,t}$ during the entire 1985–2013 period.¹⁷ The triple-differences specification is the following:

$$\begin{aligned}
SWB_{i,t} = & \alpha_1 \cdot IncomeRank_{i,t} + \alpha_2 \cdot IncomeRank_{i,t} \cdot I_t^{01-13} + \alpha_3 \cdot InternetRank_{i,t} + \\
& + \alpha_4 \cdot InternetRank_{i,t} \cdot I_t^{01-13} + \alpha_5 \cdot IncomeRank_{i,t} \cdot InternetRank_{i,t} + \\
& + \alpha_6 \cdot IncomeRank_{i,t} \cdot InternetRank_{i,t} \cdot I_t^{01-13} + X_{i,t}\beta + \delta_t + \epsilon_{i,t}
\end{aligned} \tag{4}$$

The coefficient α_2 is interpreted as the effect of the policy on individuals with the lowest Internet access, which we expect to be small or even zero. In turn, α_6 indicates how the effect of the policy changes with higher Internet access. In particular, $\alpha_6 > 0$ would indicate a greater effect on individuals with higher Internet access. Last, we can also use these two coefficients to predict the effect of higher transparency on individuals with the highest Internet access ($\alpha_2 + \alpha_6$) and the effect on the average individual ($\alpha_2 + \frac{1}{2}\alpha_6$).

3.2 Survey Data

We use data from the Norwegian Monitor Survey, which is conducted by the market research institute Ipsos MMI. The survey was conducted every second year since 1985 through a self-completion questionnaire sent by mail to a representative sample of Norwegians.¹⁸ This same dataset has been used to explore the relationship between well-being and age (Hellevik, 2002), values (Hellevik, 2003), and sustainability (Hellevik, 2015).

The final sample used in our regression analysis comprises 48,570 observations collected in 15 different years from 1985 to 2013, implying an average of 3,238 observations per survey year. This sample seems to be representative of the general population in some observable characteristics. For example, in the year 2011, 53.0% of respondents were female, the median age was 37, and the mean gross household income was \$129,684 (in current U.S. dollars). In comparison, representative statistics for Norway for that same year suggest a share of females of 50.5%, a median age of 39.1, and a mean gross household income of \$152,890.¹⁹

The surveyors did not collect information about the date when each survey was completed or mailed back, but they claim that the vast majority of the questionnaires were completed between late September and early December.²⁰ Recall that the tax agency releases the

¹⁷In other words, given that we cannot compare the change in the happiness-income gradient from 1985–1996 to 2001–2013 across individuals with high and low Internet access, we propose to compare the change in the happiness-income gradient across more educated and less educated individuals.

¹⁸For more details about the Norwegian Monitor Survey, see Hellevik (2002, 2003, 2015).

¹⁹The data sources are: Central Intelligence Agency’s World Factbook for the female share and median age, and the Euromonitor’s World Consumer Income and Expenditure Patterns for the mean household income.

²⁰The questionnaires are typically sent to the respondents in the third week of September (following a

income data for the previous fiscal year in mid-October. During that week, the search tool is used most actively. Thus, a significant share of the respondents may have completed the survey during a time when income transparency was most salient. This implies that our estimated effects of income transparency may overestimate the effects on an average day of the year.²¹

Subjective Well-Being. The main outcomes of interest are subjective questions on well-being, which are intended to proxy for experienced utility (Kahneman, Wakker, and Sarin, 1997). Two pieces of evidence support the use of subjective well-being measures with this goal. First, subjective well-being data seems to be positively correlated to more objective measures of experienced utility, such as emotional expressions (Sandvik et al., 1993), aggregate suicide rates (Di Tella, MacCulloch and Oswald, 2003), and brain activity (Urry et al., 2004). Second, subjective well-being data seems to be positively correlated with decision utility. For instance, Benjamin, Heffetz, Kimball, and Rees-Jones (2012) conducted a survey in which subjects were shown pairs of hypothetical scenarios that trade off between two or more aspects (e.g., higher income versus longer workdays). They show that, even though there are some deviations, a great majority of respondents chose the same scenario that they predicted to bring higher life satisfaction.²² And Perez-Truglia (2015) estimates consumption preferences using subjective well-being data and then shows that the expenditures choices implied by these preference parameters are largely consistent with the actual choices made by the individuals.

The Norwegian Monitor Survey includes two questions on subjective well-being, which happen to be two of the most widely used questions in the literature. The happiness question is, “Will you mostly describe yourself as: Very happy; Quite happy; Not particularly happy; Not at all happy.” Instead of arbitrarily assigning values 1, 2, 3, and 4 to the four possible answers, we employ the Probit-OLS method to assign these values (van Praag and Ferrer-i-Carbonell, 2008) and, to facilitate the interpretation of the regression coefficients, we standardized this outcome to have a mean of 0 and standard deviation of 1.²³ By construction, a higher value denotes higher happiness. As shown in Appendix A, the results are

national or local election), and the vast majority of surveys are sent back before the second week of December.

²¹On the other hand, in the fall of 2001, a significant share may have responded to the survey before the change in disclosure took place, and thus leading to an under-estimation of the effects of disclosure.

²²In subsequent work they find significant differences in the marginal rates of substitution implied by choices and subjective well-being (Benjamin, Heffetz, Kimball and Rees-Jones, 2014).

²³The Probit-OLS method consists of assigning values to the categories by fitting an ordered probit to the raw sample fractions. For example, if a fraction q reports the lowest category (not at all satisfied), that means that the highest satisfaction among the lowest category must be $\Phi^{-1}(q)$, where Φ is the cumulative distribution of a standard normal. Thus, the Probit-OLS method assigns the lowest category an score of $E[z|z < q]$, where z is distributed standard normal. The resulting values are: 1.36 (very happy), -0.17 (quite happy), -1.67 (not particular happy) and -2.79 (not at all happy).

almost identical when using other methodologies, such as coding the responses from 1 to 4, or using an Ordered Probit model instead of OLS. The life satisfaction question is, “How satisfied are you with your life? Very satisfied; Somewhat Satisfied; Neither satisfied nor dissatisfied; Slightly dissatisfied; Very dissatisfied.” This variable is coded and standardized in the same way as happiness. We use the happiness question in our baseline specifications because it was asked in all survey waves from 1985 to 2013, whereas life satisfaction was asked starting in 1999 and thus does not have enough data for some of the key falsification tests.

Income Rank. As is typical in this type of household survey, respondents were asked about their annual gross household income in categories.²⁴ The responses to this question would allow us to rank households in nine income bins.²⁵ To produce a smoother measure of income rank, we follow the standard procedure in the literature (e.g., Stevenson and Wolfers, 2008; Kahneman and Deaton, 2010). For a given year, the first step of this procedure consists in estimating an interval regression of the logarithm of income on a series of demographic characteristics, such as region and education dummies.²⁶ The second step consists of using the estimated parameters to predict the logarithm of income for each individual, conditional on belonging to the reported income bracket. Finally, we constructed the variable *Income Rank* as the proportion of households for that year with a predicted household income below that of the respondent.²⁷

Control Variables. We include the typical social and demographic characteristics employed in related studies as control variables: a gender dummy, age and age squared, four education dummies, four dummies for marital status, six dummies for household size, and four dummies for the number of working household members.

Internet Rank. We follow a two-step procedure similar to the one used for *Income Rank*. In the first step, we used respondents from 2001 to estimate a regression of the dummy *Internet Access* on the same set of socio-economic characteristics used as control variables in the happiness regressions and listed in the previous paragraph. The results from this auxiliary regression are reported in Appendix A. The regression coefficients suggest that, relative to individuals with lower Internet access, individuals with higher Internet access are

²⁴About 6% of the sample was dropped because they did not complete this question on gross household income.

²⁵The fraction of observations that fall in each of the income categories ranges from a minimum of 4% to a maximum of 16%.

²⁶The following is the list of regressors: nineteen region dummies, one gender dummy, four education dummies, four dummies for marital status, six dummies for household size, and five dummies for number of children in the household.

²⁷Intuitively, given that many households report the same income category, the imputation procedure uses information on other household characteristics that are correlated to income, such as education and marital status, to break the tie and order household within that income category from lowest to highest income.

on average richer, more likely to be female, much younger, more likely to have children and much more educated. Indeed, these correlations are largely consistent with the correlations reported in other studies of Internet access and Internet use in developed countries (File and Ryan, 2013). In the second step, we used the estimated coefficients to predict *Internet access* for 1985–2013, and constructed the variable *Internet Rank* as the proportion of respondents for that same year with a predicted access below that of the respondent.

Additional Outcome Variables. Starting in 1993, the survey included a subjective question about the self-perceived income rank: “In comparison to other Norwegians, would you say that your economic situation is...? Much worse than average; Slightly worse than average; Average; Slightly better than average; Much better than average.” We constructed the variable *Perceived Rank* with the responses to this question, which were coded and standardized following the same method than for subjective well-being. By definition, higher values of this variable denote a higher rank. Since 1985, the survey also includes the question, “Wages vary with the nature of work, education, experience, responsibilities, etc. What do you think of wage differentials in Norway today?” We constructed the variable *Redistribution Preferences* based on the answers “They are too large,” “They are adequate” and “They are too small,” which were coded and standardized following the same method than for subjective well-being. Note that this variable reflects preferences for redistribution to the extent that it measures the gap between the desired level and the perceived level of income inequality. By definition, higher values of this variable denote preferences for higher redistribution.

Last, Table 1 summarizes the definitions for the main variables, and Table 2 provides some descriptive statistics for these same variables.

4 Results

4.1 Effects of the Change in Disclosure on Subjective Well-Being

Table 3 reports the main regression results. Columns (1) through (4) correspond to the regressions with *Happiness* as the dependent variable. Column (1) presents the simplest specification, corresponding to equation (1). The coefficient on *Income Rank* measures the happiness-income gradient during 1985–2000. The estimated coefficient, 0.311, is statistically significant and precisely estimated. This implies that, during 1985–2000, going from the lowest to the highest income rank in Norway was associated with an increase in happiness of 0.311 standard deviations.²⁸ This coefficient is in the same order of magnitude as the

²⁸An alternative way to assess the magnitude of this coefficient is to compare it to some of the coefficients on the control variables: the gender gap (i.e., between women and men) amounts to 0.1 standard deviation in happiness, the mid-life crisis gap (i.e., between age 25 and 50) amounts to 0.268 standard deviations, and

coefficients reported in other studies that used similar specifications but with data for other countries.²⁹ Part of the coefficient on *Income Rank* must be picking up the effect of intrinsic utility from income, and part of this coefficient may be picking up the effects of self-image and social-image.

Column (1) of Table 3 also reports the coefficient on the interaction between *Income Rank* and *Dummy 2001–2013*, which measures the effect of the change in disclosure. The coefficient on this interaction (0.090) is positive, large and statistically significant at the 1% level. These findings suggest that the happiness-income gradient increased from 1985–2000 to 2001–2013 by an economically significant 29%, from 0.311 to 0.401.

The first concern is that the coefficient on the interaction of *Income Rank* with *Dummy 2001–2013* may not correspond to the 2001 change in disclosure, but instead results from a gradual change in this gradient that occurred over decades. To address this concern, column (2) of Table 3 shows results for the specification corresponding to equation (2), which includes the interaction between *Income Rank* and the time trend. The coefficient on the interaction between *Income Rank* and the time trend (0.002) is close to zero and statistically insignificant, whereas the coefficients on *Income Rank* and on its interaction with *Dummy 2001–2013* are very close to (and statistically indistinguishable from) the corresponding coefficients from the baseline specification in column (1). These results suggest that the change in the happiness-income gradient corresponds to a discontinuous change around 2001.

In turn, column (3) of Table 3 presents results from the specification corresponding to equation (3), which introduces interactions of *Income Rank* with *Dummy 2001–2013* and *Dummy 1997–2000*. The coefficients on *Income Rank* (0.315) and its interaction with *Dummy 2001–2013* (0.102) reported in column (2) are very similar to the corresponding coefficients from column (1). Indeed, their pairwise differences are statistically insignificant. Also, as expected, the coefficient on the interaction of *Income Rank* with *Dummy 1997–2000* is close to zero (0.002) and statistically insignificant. Moreover, there is an statistically significant difference (p-value=0.04) between the coefficients on the interactions with *Dummy 1997–2000* (0.002) and *Dummy 2001–2013* (0.090).

Figure 3.a takes the last specification a step further by means of an event-study analysis. This figure shows the evolution of the happiness-income gradient over the years around the

the widower gap (i.e., between married and widowers) amounts to 0.367 standard deviations.

²⁹For example, results reported in Table 2 from Stevenson and Wolfers (2008) suggest that, using data for a number of countries from the World Values Survey, the ordered probit regression of happiness on the logarithm of household income yields a coefficient of 0.244 (SE 0.008). Estimating the same regression with our Norwegian data yields a coefficient of 0.307 (SE 0.008), which is in the same order of magnitude – we would not expect them to be exactly equal, because Norway is not representative of all the countries in the World Value Survey and because there are differences in how income and subjective well-being are measured across these two datasets.

change in disclosure. Each coefficient corresponds to the change in the happiness-income gradient, relative to 1997–2000. By construction, the coefficient for 1997–2000 is normalized to zero. Figure 3.a suggests that the happiness-income gradient had been stable during 1985–2000 and increased sharply in 2001. According to the coefficients from Figure 3.a, we cannot reject the null hypothesis that the change in the happiness-income gradient remained constant over 2001–2013. This finding is consistent with the discussion from section 2 that the increase in income transparency persisted at roughly the same level from 2001 to 2013.³⁰

Another concern is that the effect on the happiness-income gradient may not result from the change in disclosure, but instead from something else that happened at the same time. To the best of our knowledge, there were no major events that could explain these patterns. For instance, in 2001, there were no important changes to the income tax schedule or welfare benefits. To address this concern more directly, column (3) of Table 3 reports the results from the triple-differences design of equation (4). The evidence is consistent with the hypothesis that higher income transparency is responsible for the change in the happiness-income gradient. First, the coefficient on the interaction between *Income Rank* and *Dummy 2001–2013* is close to zero (0.001), statistically insignificant, and precisely estimated. This coefficient suggests that the change in disclosure had no effect on individuals with the lowest Internet Rank.³¹ Second, the coefficient on the triple interaction between *Income Rank*, *Dummy 2001–2013*, and *Internet Rank* (0.182) is positive, large and statistically significant. This coefficient indicates that the effect of income transparency increases as *Internet Rank* increases. For instance, the estimated effect on an individual with the highest *Internet Rank* is 0.183 (p-value<0.01).³²

As an additional robustness check, we can compare the effects of happiness with the effects on life satisfaction. Even though happiness and life satisfaction are often treated as interchangeable, they are supposed to capture different concepts: happiness is more affective, whereas satisfaction is more evaluative (Kahneman and Deaton, 2010). Given that self-image and social-image are believed to be important for both affective and evaluative reasons, we expect to find effects on life satisfaction that are qualitatively consistent with the effects on happiness. One limitation, however, is that the life satisfaction question was added to the survey in 1999. Thus, we can estimate only the baseline specification from equation (1).

Column (5) of Table 3 shows the regression results using life satisfaction instead of happiness as the dependent variable. The coefficient on *Income Rank* (0.585) is larger than and

³⁰Additionally, if the effects are attributed to income comparisons, this finding would be consistent with the evidence from Di Tella, Haisken-De New and MacCulloch (2010) of no hedonic adaptation to status.

³¹For instance, in the bottom-5% of *Internet Rank* as of 2001, only 8% had Internet access.

³²For instance, in the top-5% of *Internet Rank* as of 2001, 100% had Internet access. Also, for an individual with an average *Internet Rank*, the estimated effect on the happiness-income gradient is 0.092 (p-value<0.01), which, as expected, is close to the effect reported in the baseline specification (0.090, from column (1)).

statistically different from the corresponding coefficient reported in column (1) for happiness (0.311). This difference is expected, given that these two outcomes should measure different concepts and that they even use different scales. Consistent with our results, several studies find that income is more strongly associated with evaluative measures, such as life satisfaction, than with affective measures, such as happiness (Kahneman and Deaton, 2010). More important, column (5) shows that the coefficient on the interaction between *Income Rank* and *Dummy 2001–2013* (0.121) is positive, large and statistically significant at the 5%. These estimates imply that the higher income transparency increased the life satisfaction–income gradient by 21%, from 0.585 to 0.706. Moreover, the magnitude of the effects seems to be the same for life satisfaction and happiness: we cannot reject the null hypothesis that the proportional effect on the life satisfaction–income gradient (21%, SE 11%) is equal to the corresponding effect on the happiness–income gradient (29%, SE 11%).

We also present results in a placebo country, Germany. Germans were not affected by the change in disclosure, so there should be no change in the happiness–income gradient in 2001. For this, we employ data from the German Socio-Economic Panel (GSOEP) survey, which was collected every year from 1985 to 2013. Because the total number of observations for the GSOEP data (105,738) is more than twice as large as for the Norwegian Monitor (48,570), the estimates for Germany are more precisely estimated than the corresponding estimates for Norway. In the GSOEP data, we measure life satisfaction based on the question, “How satisfied are you with your life, all things considered?” Responses are measured on a 11-point scale ranging from “Completely Dissatisfied” (0) to “Completely Satisfied” (10). We coded and standardized this variable as with the other subjective scores. We reproduced the same regression specification using all the same control variables that were constructed for the Norwegian dataset.

Column (8) of Table 3 reports the results for Germany. The coefficient on *Income Rank*, 0.494, is in the same order of magnitude as the corresponding coefficient for Norway (0.585, from column (5)). These two coefficients should not be equal, because these are two different countries and because the life satisfaction questions differ. Most important, column (8) indicates that, unlike in Norway, in Germany there was no significant change in the life satisfaction–income gradient in 2001: the coefficient on the interaction with *Dummy 2001–2013* (0.014) is close to zero, statistically insignificant, and precisely estimated. These coefficients imply that the life satisfaction–income gradient increased by an insignificant 2.9% (SE 4.6%) since 2001. Furthermore, the difference between this 2.9% effect on life satisfaction for Germany (from column (8)) and the corresponding 21% effect for Norway (from column (5)) is statistically significant at the 1% level. Last, Figure 3.b reproduces the event-study analysis for Germany. This figure suggest that, unlike in Norway, in Germany there was no

significant change in the life-satisfaction gradient around 2001.

Appendix A presents a number of additional robustness checks. For example, it shows that the results are robust to using ordered probit instead of OLS regressions, using local income ranks instead of national income ranks, and using sampling weights to make the survey data more representative.

In addition to its effect on the happiness-income gradient, it may be useful to study the effect of higher transparency on average happiness. As discussed in the model from Appendix C, the expected effect of higher transparency on average well-being has an ambiguous sign and is likely to be close to zero. The empirical identification of this average effect, however, is more challenging. Appendix A.2 presents results from a differences-in-differences estimator that is based on the assumption that the change in disclosure had a larger effect on individuals with higher Internet access. These results suggest that the change in disclosure did not have a significant effect on average happiness and average life satisfaction. When taken together with the findings from this section, these additional results suggest that higher income transparency resulted in a redistribution of well-being from the poor to the rich.

4.2 Effects of the Change in Disclosure on Self-Perceptions of Income Rank and Preferences for Redistribution

According to the self-image mechanism (see Appendix C for a discussion), income transparency increases the gradient between self-perceived income rank and actual income rank. We can assess the plausibility of the self-image mechanism by testing this hypothesis directly. To do so, we reproduce the regression analysis using the measure of self-perceived relative income instead of subjective well-being as the dependent variable.

Column (6) of Table 3 presents the results with *Perceived Rank* as the dependent variable. The coefficient on *Income Rank* (2.128) is positive, large and statistically significant at the 1% level. This coefficient implies that, prior to 2001, going from the poorest to the richest household was associated with an increase in self-perceived income rank of 2.128 standard deviations. On the one hand, these results suggest a strong association between self-perceived and actual income rank. On the other hand, the implied correlation between actual and self-perceived income rank is 0.46, which falls significantly short from 1 and thus is suggestive of potentially large misperceptions.³³

³³Part of this misalignment could be due to mis-reporting of actual income or mis-reporting of self-perceived income. Additionally, part of the misalignment could be explained by the fact that *Perceived Rank* is based on a subjective scale. For example, two individuals in the 58% percentile of the income distribution may respond differently to the subjective question on self-perceived rank because one could think that “slightly above average” corresponds to the range 50%-55% of the income distribution, while the other may think that it corresponds to 50%-60%.

Column (6) of Table 3 also shows that the coefficient on the interaction between *Income Rank* and *Dummy 2001–2013* (0.228) is positive, large and statistically significant at the 1% level, whereas the coefficient on the interaction between *Income Rank* and *Dummy 1997–2000* is small and statistically insignificant. These results imply that the higher income transparency increased the gradient between self-perceived income rank and actual income rank by 11% (from 2.128 to 2.356), which is both statistically and economically significant. In other words, self-perceptions of income rank became 11% more accurate as a result of the change in disclosure.

If individuals correct their misperceptions about their own relative income, then they should adjust their preferences for redistribution accordingly.³⁴ More precisely, the gradient between redistribution preferences and actual income rank should increase. Again, to test this hypothesis we reproduce the regression analysis using preferences for redistribution instead of subjective well-being as the dependent variable. Column (7) of Table 3 presents the results with *Redistribution Preferences* as the dependent variable. The coefficient on *Income Rank* (-0.800) is negative, large and statistically significant at the 1% level. This coefficient implies that going from the poorest to the richest household is associated with a decrease in redistribution preferences of 0.8 standard deviations. Column (7) also shows that the coefficient on the interaction between *Income Rank* and *Dummy 2001–2013* (-0.107) is negative and statistically significant at the 1% level, whereas the coefficient on the interaction between *Income Rank* and *Dummy 1997–2000* is close to zero and statistically insignificant. These coefficients imply that higher income transparency increased the gradient between redistribution preferences and actual income rank by 13% (from 0.800 to 0.907). As expected, this effect is similar to and statistically indistinguishable from the 11% increase in the gradient between self-perceived and actual income rank.

On the one hand, the significant effect on self-perceived income rank suggests that at least part of the effects of income transparency on well-being can be attributed to the self-image mechanism. On the other hand, the magnitude of this effect suggests that self-image is not large enough to explain all the effects of income transparency on well-being on its own. Consider the extreme assumption that intrinsic utility and self-image are the only factors driving the relationship between well-being and income. In that case, we predict that the 11% increase in the accuracy of self-perceived income rank will raise the gradient between well-being and actual income rank by 11% or less.³⁵ However, this predicted effect falls

³⁴For instance, Cruces, Perez-Truglia, and Tetaz (2013) and Karadja, Mollerstrom, and Seim (2015) show evidence from survey experiments that, when provided with objective information about their true position in the income distribution, subjects change their stated preferences for redistribution.

³⁵If intrinsic utility plays no role, then we would predict an effect of 11%. And if intrinsic utility plays a role, then we would predict an effect of less than 11%.

short of the observed effect of 29% and 21% on the happiness-income gradient and the life satisfaction-income gradient. Thus, the evidence suggests that other mediating factors that differ from self-image, such as social-image, must also play a significant role.³⁶

5 Measuring the Value of Self-Image and Social-Image

The previous section presented evidence about the causal effect of the change in disclosure on well-being. In this section, we assume that the estimated effects are entirely explained by income comparisons and use these estimates for back-of-the-envelope calculations of the value of self-image and social-image.

Let $\nu_t \in [0, 1]$ denote the visibility of income in year t (i.e., the probability that individuals observe the incomes of others). According to the model from Appendix C, an individual's utility can be expressed as follows:

$$SWB_{i,t} = (\beta_1 + \beta_2 \cdot \nu_t) \cdot IncomeRank_{i,t} \quad (5)$$

The coefficient β_1 measures the marginal utility from income through consumption, and $\beta_2 \cdot \nu_t$ measures the marginal utility from income through self-image and social-image. Intuitively, in a world where all incomes are unobservable ($\nu_t = 0$), an increase in one's income cannot increase the utility from self-image or social-image. On the other extreme, increasing one's income has the highest possible effect on self-image and social-image when incomes are perfectly visible ($\nu_t = 1$).

Let $\bar{\nu}_{t < 2001}$ and $\bar{\nu}_{t \geq 2001}$ denote the visibility before 2001 and after 2001, respectively. Note that $\bar{\nu}_{t < 2001}$ must be greater than zero, because even when the tax records were private, individuals could use other means to learn about the incomes of social contacts and about the income distribution. For instance, individuals could learn about the income distribution from school, from the media, or by talking with others about wages and consumption. Also, individuals could reveal their own income to their social contacts, in a probabilistic sense, through conspicuous consumption and statistical discrimination (e.g., Heffetz, 2011). Similarly, $\bar{\nu}_{t \geq 2001}$ must be lower than 1, because even when the tax records were easily accessible online, there was still a small cost in attention, memory, and time to search those records. Thus, individuals did not search for the incomes of everyone with whom they interacted.

We can measure the importance of income comparisons as $s_t = \frac{\beta_2 \cdot \nu_t}{\beta_1 + \beta_2 \cdot \nu_t}$, which is the share of the happiness-income gradient that can be explained by self-image and social-image.

³⁶This analysis is related to Senik (2009), who uses subjective well-being data as well as other subjective questions in order to disentangle comparisons between external and internal benchmarks.

Combining (1) and (5) and re-arranging:

$$s_{t<2001} = \frac{\frac{\alpha_2}{\alpha_1}}{\frac{\bar{\nu}_{t>2001} - \bar{\nu}_{t<2001}}{\bar{\nu}_{t<2001}}}, \quad s_{t\geq 2001} = \frac{1 + \frac{\frac{1}{\bar{\nu}_{t\geq 2001} - \bar{\nu}_{t<2001}}}{\bar{\nu}_{t<2001}}}{1 + \frac{\frac{1}{\alpha_2}}{\alpha_1}} \quad (6)$$

The value of self-image and social-image depends on two parameters: $\frac{\alpha_2}{\alpha_1}$ and $\frac{\bar{\nu}_{t\geq 2001} - \bar{\nu}_{t<2001}}{\bar{\nu}_{t<2001}}$. The first parameter is the proportional growth in the happiness-income gradient as a result of the change in disclosure in 2001. This first parameter was estimated in the previous section. The second parameter is the effect of the change in disclosure on income visibility.³⁷ Because we do not have an estimate of this second parameter, we present results assuming different values for it.

First, we estimate a lower bound for the value of income comparisons. Note that $s_{t\geq 2001}$ is strictly increasing in $\bar{\nu}_{t<2001}$. Thus, by assuming $\bar{\nu}_{t<2001} = 0$, we can estimate a lower bound on $s_{t\geq 2001}$. This is a conservative lower bound because, as previously discussed, it is highly unlikely that income information was completely private before 2001. Assuming that $\bar{\nu}_{t<2001} = 0$ implies that self-image and social-image explain at least 22% of the happiness-income gradient after 2001 (i.e., $s_{t\geq 2001} = \frac{0.090}{0.311+0.090}$) and that they explain at least 17% of the life satisfaction-income gradient after 2001 (i.e., $s_{t\geq 2001} = \frac{0.121}{0.585+0.121}$). These results suggest that the value of income comparisons is bound to be economically significant.

Second, we estimate an upper bound for the value of income comparisons. As $\frac{\bar{\nu}_{t\geq 2001} - \bar{\nu}_{t<2001}}{\bar{\nu}_{t<2001}}$ approaches $\frac{\alpha_2}{\alpha_1}$ from above, both $s_{t<2001}$ and $s_{t\geq 2001}$ converge to 1. That is, a change in visibility of $\frac{\alpha_2}{\alpha_1}$ would imply that social-image and self-image explain the entire relationship between income and well-being. In the case of happiness, we would need to assume that visibility increased by 29% as a result of the change in disclosure. In the case of life satisfaction, we would have to assume that visibility increased by 21%. Given all the evidence about the widespread use of the search tool, it seems somewhat unlikely, although plausible, that the publication of tax records increased income visibility by just 21%. In this sense, our results suggest that income comparisons are not the only factor mediating the effect of income on well-being.

Third, we discuss an intermediate scenario based on the assumption that income visibility doubled because of the 2001 event. In that case, self-image and social-image explain 29% of the happiness-income gradient before 2001 and 47% of this gradient after 2001. They also explain 21% of the life satisfaction-income gradient before 2001 and 34% of this gradient after 2001. Given that income visibility in most of the world may be more comparable to

³⁷The formula for $s_{t<2001}$ from (6) can be interpreted as a Wald estimate: i.e., the ratio between the effect on the happiness-income gradient (i.e., the reduced form effect) and the effect on visibility (i.e., the first stage effect).

income visibility in Norway before 2001, we focus on the value of income comparisons before 2001. These estimates imply that self-image and social-image account for 21%–29% of the relation between subjective well-being and income. This is a significant share, but it still implies that absolute income is about twice as important for well-being as relative income. Even if we assumed that the change in disclosure increased visibility by just 50%, absolute income remains roughly as important for well-being as relative income.

Last, we qualify some of these back-of-the-envelope calculations. First and most important, these results depend on the assumption that the estimated effects of income transparency on well-being are entirely explained by self-image and social-image. This assumption may lead to an over-estimation or an under-estimation of the value of self-image and social-image, depending on whether the confounding factors have a positive or negative net effect on the happiness-income gradient, respectively. It is important to note that we interpret social-image in a broad sense, as in the rest of the literature (Bénabou and Tirole, 2006). For instance, social-image utility could represent the psychological utility from merely thinking that others can observe that one is rich. And social-image utility could also represent the consumption of non-market goods (e.g., dating and business opportunities) that are allocated to richer individuals in social interactions.

Regarding the external validity of the findings, we must note that Norway is among the richest countries in the world. If income comparisons became relatively more important as countries get richer, as has been suggested in the literature (Clark, Frijters, and Shields, 2008), then our results for Norway would over-estimate the value of self-image and social-image in the rest of the world.

6 Conclusions

In 2001, Norwegian tax records became easily accessible online, allowing individuals to observe each other’s incomes. We proposed that, because of self-image and social-image concerns, higher income transparency can increase the differences in well-being between rich and poor. Using survey data and multiple identification strategies, we present evidence that higher income transparency caused an increase of 29% in the happiness-income gradient and an increase of 21% in the life satisfaction-income gradient. These findings suggest that the change in disclosure had a large effect on the well-being of Norwegians. Moreover, assuming that these effects are caused only by income comparisons, the estimates imply that the value of self-image and social-image is bound to be large.

We conclude by discussing some implications for the design of disclosure policies. Detractors of open disclosure in Norway have acknowledged its potential for creating unintended

social effects. Until now, there has been only anecdotal evidence.³⁸ Our findings suggest that disclosing income information can have large effects on the well-being of the individuals whose information is disclosed. These effects should be considered in the cost-benefit analysis when choosing how to disclose sensitive information, such as tax records, in Norway and in the rest of the world.

The government can disclose sensitive data in a way that minimizes these unintended costs and preserves the intended benefits and the principle of transparency. The policy change of 2014 appears to be a successful step in this direction. Individuals seem to avoid asking others face to face about their incomes because asking them would entail social sanctions. In that case, making the searches non-anonymous may introduce these social sanctions and then reduce the number of searches that are only for social comparisons. Consistent with this view, in 2014, the number of searches for online tax records dropped by 88% immediately after they were made non-anonymous. Indeed, immediately after this change in policy, the number of users visiting the website remained roughly unchanged, but these users switched from searching for the incomes of others to searching for whomever was searching for their own incomes.³⁹

³⁸Some detractors of open disclosure also argued to dislike the policy on ethical grounds, and others reported to be afraid that the information could be used by criminals (although, to the best of our knowledge, there is no evidence supporting this concern).

³⁹Source: “«Ingen» sjekker skattelistene lenger – frykter å bli uthengt som snokere,” NRK, October 28, 2014.

References

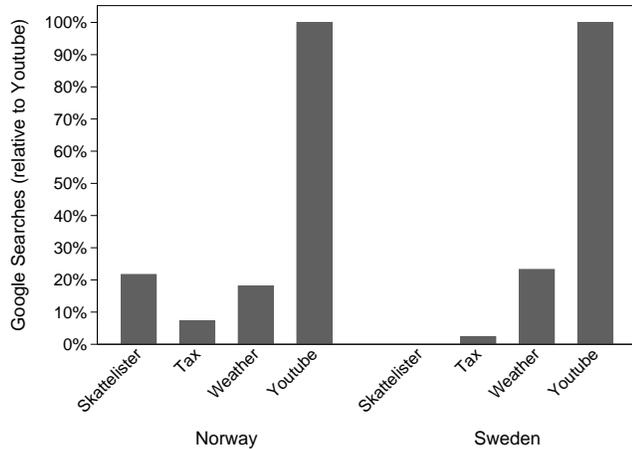
- [1] Balassa, B. (1964), “The Purchasing Power Parity Doctrine: A Reappraisal,” *Journal of Political Economy*, Vol. 72 (6), pp. 584–596.
- [2] Bénabou, R.J.M. and J. Tirole. (2006), “Incentives and Prosocial Behavior,” *American Economic Review*, Vol. 96 (5), pp. 1652-1678.
- [3] Benjamin, D.J.; Heffetz, O.; Kimball, M.S. and Rees-Jones, A. (2012), “What Do You Think Would Make You Happier? What Do You Think You Would Choose?” *American Economic Review*, Vol. 102 (5), pp. 2083–2110.
- [4] Benjamin, D.J.; Heffetz, O.; Kimball, M.S. and Rees-Jones, A. (2014), “Can Marginal Rates of Substitution Be Inferred From Happiness Data? Evidence from Residency Choices.” *American Economic Review*, Vol. 104 (11), pp. 3498-3528.
- [5] Bø, E.E.; Slemrod, J. and Thoresen, T.O. (2015), “Taxes on the Internet: Deterrence Effects of Public Disclosure,” *American Economic Journal: Economic Policy*, Vol. 7 (1), pp. 36-62.
- [6] Boskin, M. and Sheshinski, E. (1978), “Optimal Redistributive Taxation When Individual Welfare Depends on Relative Income,” *Quarterly Journal of Economics*, Vol. 92 (4), pp. 589-601.
- [7] Card, D.; Mas, A.; Moretti, E. and Saez, E. (2012), “Inequality at Work: The Effect of Peer Salaries on Job Satisfaction,” *American Economic Review*, Vol. 102 (6), pp. 2981-3003.
- [8] Chetty, R.; Hendren, N.; Kline, P. and Saez, E. (2014), “Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States,” *Quarterly Journal of Economics*, Vol. 129 (4), pp. 1553-1623.
- [9] Clark, A.E.; Frijters, P. and Shields, M.A. (2008), “Relative Income, Happiness, and Utility: An Explanation for the Easterlin Paradox and Other Puzzles,” *Journal of Economic Literature*, Vol. 46 (1), pp. 95-144.
- [10] Clark, A.E. and Senik, C. (2010), “Who compares to whom? The anatomy of income comparisons in Europe,” *Economic Journal*, Vol. 120, pp. 573-594.
- [11] Clark, A.E.; Kristensen, N. and Westergård-Nielsen, N. (2009), “Economic Satisfaction and Income Rank in Small Neighbourhoods,” *Journal of the European Economic Association*, Vol. 7, pp. 519-527.
- [12] Cruces, G.; Perez-Truglia, R. and Tetaz, Martin (2013), “Biased Perceptions of Income Distribution and Preferences for Redistribution: Evidence from a Survey Experiment,” *Journal of Public Economics*, Vol. 98, pp. 100-112.
- [13] De Neve, J.E. and Oswald, A.J. (2012), “Estimating the influence of life satisfaction and positive affect on later income using sibling fixed effects,” *Proceedings of the National Academy of Sciences*, Vol. 109 (49), pp. 19953-19958.
- [14] Deaton, A. and Stone, A. (2013), “Two Happiness Puzzles,” *American Economic Review*:

- Papers & Proceedings, Vol. 103 (3), pp. 591-597.
- [15] Di Tella, R.; MacCulloch, R. and Oswald, A. (2003), "The Macroeconomics of Happiness," *Review of Economics and Statistics*, Vol. 85 (4), pp. 809-27.
- [16] Di Tella, R; Haisken-De New, J. and MacCulloch, R. (2010), "Happiness Adaptation to Income and to Status in an Individual Panel," *Journal of Economic Behavior & Organization*, Vol. 76 (3), pp. 834–852.
- [17] Easterlin, R.A. (1974), "Does economic growth improve the human lot? Some empirical evidence," *Nations and households in economic growth*, Vol. 89, pp. 89-125.
- [18] Ferrer-i-Carbonell, A. (2005), "Income and Well-Being: An Empirical Analysis of the Comparison Income Effect," *Journal of Public Economics*, Vol. 89, pp. 997–1019.
- [19] File, T. and Ryan, C. (2014), "Computer and Internet Use in the United States: 2013," *American Community Survey Report*.
- [20] Frank, R.H. (1985), "The Demand for Unobservable and Other Positional Goods," *The American Economic Review*, Vol. 75, pp. 101-116.
- [21] Gerber, A.S.; Green, D.P. and Larimer, C.W. (2008), "Social Pressure and Voter Turnout: Evidence from a Large-scale Field Experiment," *American Political Science Review*, Vol. 102 (1), pp. 33-48.
- [22] Hagerty, M.R. and Veenhoven, R. (2003), "Wealth and Happiness Revisited – Growing National Income Does Go with Greater Happiness," *Social Indicators Research*, Vol. 64, pp. 1–27.
- [23] Heffetz, O. (2011), "A Test of Conspicuous Consumption: Visibility and Income Elasticities," *Review of Economics and Statistics*, Vol. 93 (4), pp. 1101-1117.
- [24] Hellevik, O. (2002), "Age differences in value orientation – life cycle or cohort effect?" *International Journal of Public Opinion Research*, Vol. 14 (3), pp. 286–302.
- [25] Hellevik, O. (2003), "Economy, values and happiness in Norway," *Journal of Happiness Studies*, Vol. 4 (3), pp. 243-283.
- [26] Hellevik, O. (2015a), "Is the good life sustainable? A three decade study of values, happiness and sustainability in Norway," in Mueller, M.L. and Syse, K.V.L. (eds.), *Sustainable Consumption and the Good Life*. London & New York: Routledge.
- [27] Kahneman, D.; Wakker, P. and Sarin, R. (1997), "Back to Bentham? Explorations of Experienced Utility," *Quarterly Journal of Economics*, Vol. 112 (2), pp. 375-405.
- [28] Kahneman, D. and Deaton, A. (2010), "High income improves evaluation of life but not emotional well-being," *Proceedings of the National Academy of Sciences*, Vol. 107 (38), pp. 16489-16493.
- [29] Karadja, M.; Mollerstrom, J. and Seim, D. (2015), "Richer (and Holier) than Thou? The Effect of Relative Income Improvements on Demand for Redistribution," *Mimeo*.
- [30] Luttmer, E.F.P. (2005), "Neighbors as Negatives: Relative Earnings and Well-Being," *Quar-*

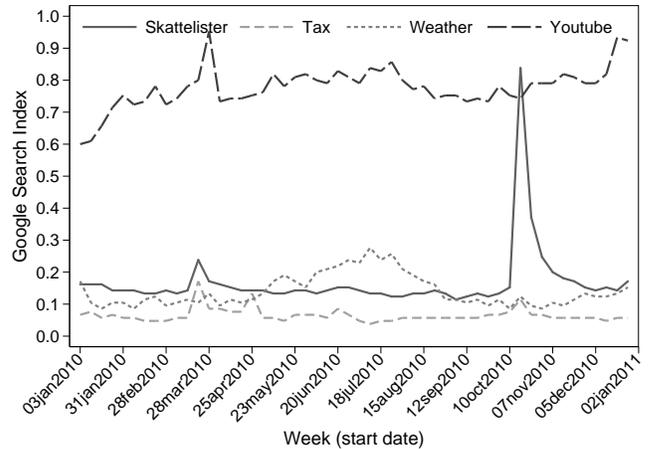
- terly *Journal of Economics*, Vol. 120 (3), pp. 963-1002.
- [31] Norway Minister of Finance (2014), “Høringsnotat om innstramminger i reglene om offentlige skattelister,” published January 24, 2014.
- [32] Perez-Truglia, R. and Cruces, G. (2014), “Partisan Interactions: Evidence from a Field Experiment in the United States.” Available at SSRN: <http://ssrn.com/abstract=2427148>.
- [33] Perez-Truglia, R. (2015), “A Samuelsonian Validation Test for Happiness Data,” *Journal of Economic Psychology*, Vol. 49, pp. 74–83.
- [34] Perez-Truglia, R. and Troiano, U. (2015), “Shaming Tax Delinquents: Theory and Evidence from a Field Experiment in the United States,” NBER Working Paper No. 21264.
- [35] Rabin, M. (1994), “Cognitive Dissonance and Social Change,” *Journal of Economic Behavior and Organization*, Vol. 23, pp. 177-194.
- [36] Rege, M. and Solli, I.F. (2015), “Lagging Behind the Joneses: The Impact of Relative Earnings on Job Separation,” Working paper.
- [37] Samuelson, P.A. (1964), “Theoretical Notes on Trade Problems,” *Review of Economics and Statistics*, Vol. 46 (2), pp. 145–154.
- [38] Sandvik, E.; Diener, E. and Seidlitz, L. (1993), “Subjective Well-Being: The Convergence and Stability of Self-Report and Non-self-Report Measures,” *Journal of Personality*, Vol. 61 (3), pp. 317-42.
- [39] Senik, C. (2004), “When Information Dominates Comparison. Learning from Russian Subjective Panel Data,” *Journal of Public Economics*, Vol. 88, pp. 2099-2133.
- [40] Senik, C. (2009), “Direct Evidence on Income Comparison and their Welfare Effects,” *Journal of Economic Behavior and Organization*, Vol. 72, pp. 408-424.
- [41] Stephens-Davidowitz, S. (2014), “The cost of racial animus on a black candidate: Evidence using Google search data,” *Journal of Public Economics*, Vol. 118, pp. 26–40.
- [42] Stevenson, B. and Wolfers, J. (2008), “Economic Growth and Subjective Well-Being: Reassessing the Easterlin Paradox,” NBER Working Paper No. 14282.
- [43] Teknologiradet (2010), “Innspill til komitébehandling om offentliggjøring av skattelister,” Mimeo.
- [44] Thoresen, T.O.; Bø, E.E.; Fjærli, E. and Halvorsen, E. (2012), “A Suggestion for Evaluating the Redistributive Effects of Tax Changes: With an Application to the 2006 Norwegian Tax Reform,” *Public Finance Review*, Vol. 40 (3), pp. 303–338.
- [45] Urry, H.L.; Nitschke, J.B.; Dolski, I.; Jackson, D.C.; Dalton, K.M.; Mueller, C.J.; Rosenkranz, M.A.; Ryff, C.D.; Singer, B.H. and Davidson, R.J. (2004), “Making a Life Worth Living: Neural Correlates of Well Being,” *Psychological Science*, Vol. 15 (6), pp. 367-372.
- [46] van Praag, B.M.S. and Ferrer-i-Carbonell, A. (2008), “Happiness Quantified: A Satisfaction Calculus Approach.” Oxford: Oxford University Press.

Figure 1: Interest in Tax Records Measured by Google Searches

a. 2010 Annual Searches, Norway and Sweden



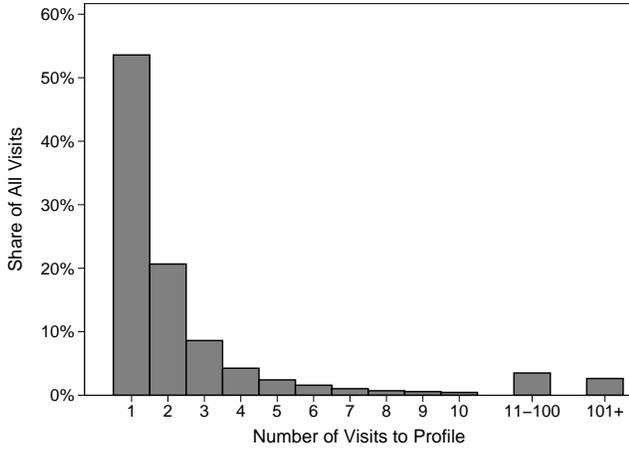
b. 2010 Weekly Searches, Norway



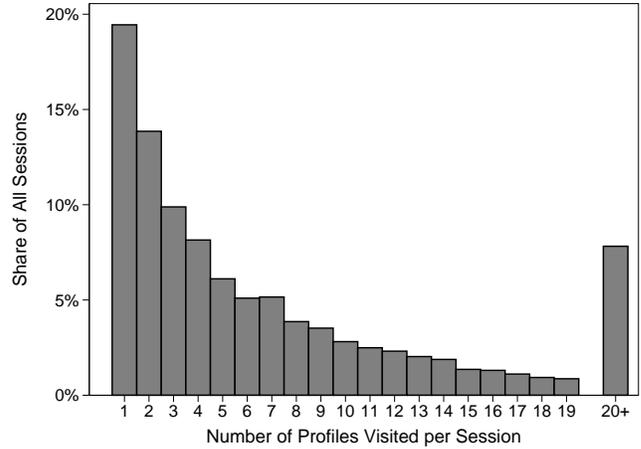
Notes: Google Trends data for 2010. (a) Annual number of Google searches for each category of keywords, as a percentage of searches in Youtube category. The keywords for Youtube are always “youtube.” The rest of the keywords are as follows. Norway: “skattelister+skattelistene” (Skattelister), “skatt+skatter” (Tax) and “yr+ver” (Weather), where “yr” corresponds to the name of the most popular website about weather in the country. Sweden: “skatt+skatter” (Tax) and “väder” (Weather). (b) Weekly number of searches for each keyword category in Norway in 2010, normalized so that total searches all categories sum up to 1 in the first week of 2010.

Figure 2: Descriptive Statistics about Search Behavior in Tax Records

a. Distribution of Profile Popularity

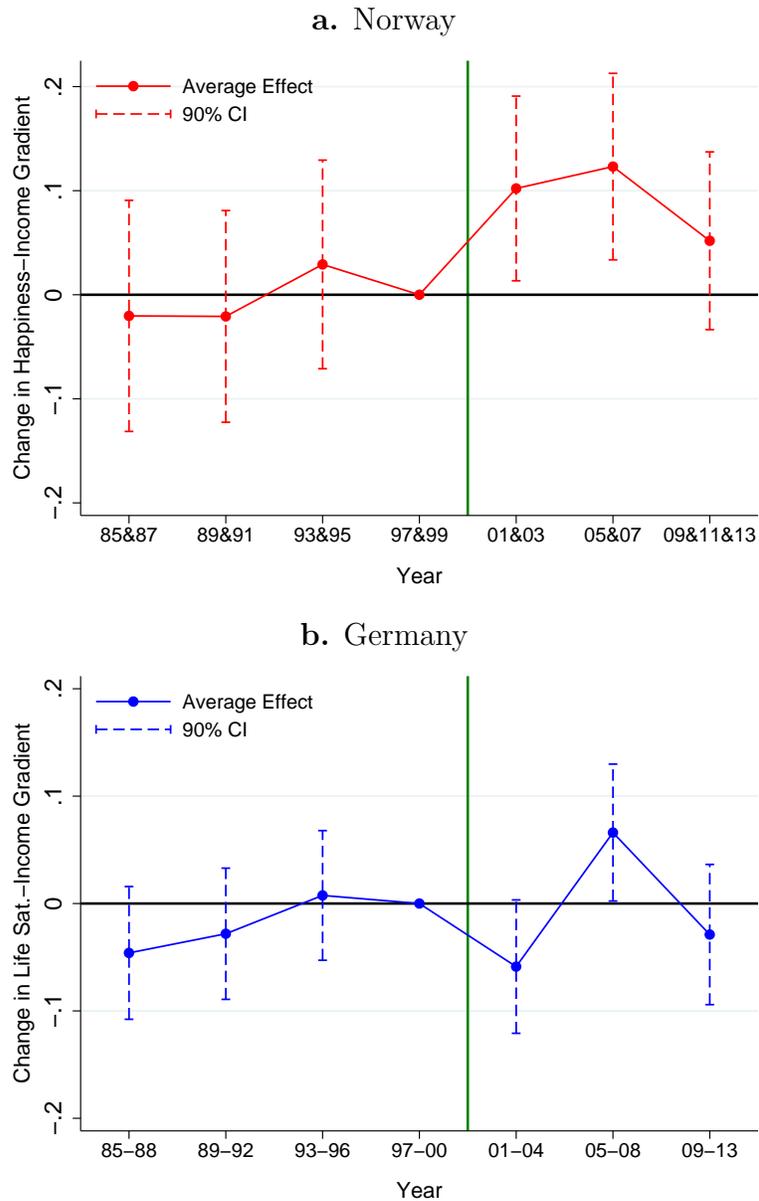


b. Profiles Visited per Session



Notes: Browsing behavior in one website that offered a tool to search the Norwegian tax records. This browsing data originates from proprietary data corresponding to a panel of Internet users. The number of visits to a profile corresponds to the number of times that the users visited the unique URL corresponding to that profile. (a) This graph shows how the total share of visits to profiles are distributed among profiles with different popularity, for profiles that have been visited at least once. For example, 20% of the total visits are made to profiles which are visited exactly twice. Data corresponding to 2010. (b) Histogram of the number of profiles visited per session, for sessions with at least one profile visited - for example, almost 20% of the sessions consist of a visit to a single profile. Data corresponding to the release date for the data on incomes corresponding to the 2009 tax calendar: October 20, 2010. A session begins when the user opens the Internet browser and finishes when the user closes the browser.

Figure 3: Event-Study Analysis: Evolution of Happiness-Income Gradient



Notes: Evolution of the gradient between well-being and income before and after the 2001 change in disclosure (represented by the green vertical line). Each coefficient corresponds to the change in the gradient between subjective well-being and *Income Rank* relative to the period 1997–2000 (by construction, the coefficient for these years is normalized to zero). *Happiness* and *Life Satisfaction* correspond to responses to subjective questions normalized to have mean 0 and standard deviation of 1, with higher values denoting higher happiness/satisfaction. *Income Rank* denotes the position of the respondent’s household relative to all the other respondents for that year, from 0 to 1. All regressions include the following control variables: year dummies, age and age squared, one gender dummy, four education dummies, four dummies for marital status, number of working household members and six dummies for household size. Panel (a) is based on 48,570 observations from the Norwegian Monitor Survey, collected every second year in 1985–2013. See Table 1 for more detailed data definitions and Table 2 for descriptive statistics. Panel (b) is based on 105,738 observations from the German Socio-Economic Panel Survey, collected every year in 1985–2013.

Table 1: Summary of Data Definitions for Main Variables, Norwegian Monitor Survey

Variable Name	Definition
<i>Happiness</i>	Based on question: “Will you mostly describe yourself as: Very happy; Quite happy; Not particularly happy; Not at all happy.” These 4 categories were assigned values using the Probit-OLS method, and then standardized so that they have mean 0 and standard deviation 1. Higher values denote higher happiness.
<i>Income Rank</i>	Estimated position in the national distribution of household gross income in a given year, from 0 (lowest income in the country) to 1 (highest income in the country). This rank is based on the following question: “What would you estimate the household’s total gross income? That is, all total income before taxes and deductions: Less than NKR100,000; NKR100,000-199,000; NKR200,000-299,000; NKR300,000-399,000; NKR400,000-499,000; NKR500,000-599,000; NKR600,000-799,000; NKR800,000-999,000; Above NKR1,000,000.” Values within bins are imputed following Kahneman and Deaton (2010).
<i>Life Satisfaction</i>	Based on question: “How satisfied are you with your life? Very satisfied; Somewhat Satisfied; Neither satisfied nor dissatisfied; Slightly dissatisfied; Very dissatisfied.” These 5 categories were assigned values using the Probit-OLS method, and then standardized so that they have mean 0 and standard deviation 1. Higher values denote higher satisfaction.
<i>Perceived Rank</i>	Based on question: “In comparison to other Norwegians, would you say that your economic situation is...? Much worse than average; Slightly worse than average; As average; Slightly better than average; Much better than average.” These 5 categories were assigned values using the Probit-OLS method, and then standardized so that they have mean 0 and standard deviation 1. Higher values denote higher rank.
<i>Redistribution Preferences</i>	Based on question: “Wage vary with the nature of work, education, experience, responsibilities, etc. What do you think of wage differentials in Norway today? They are too large; They are adequate; They are too small; Not Sure.” The category “Not sure” was treated as missing. The remaining 3 categories were assigned values using the Probit-OLS method, and then standardized so that they have mean 0 and standard deviation 1. Higher values denote preferences for more redistribution.
<i>Internet Access</i>	Dummy variable taking the value 1 if the individual responds affirmatively to at least one of the following questions: “Do you have Internet access at home? Do you have Internet access at work? Do you have Internet access at your school or university? Do you have Internet access elsewhere?”
<i>Internet Rank</i>	Estimated position in the national distribution of predicted probability of <i>Internet access</i> in a given year, from 0 (lowest predicted Internet access in the country) to 1 (highest). Based on a regression of <i>Internet Access</i> on a set of individual characteristics (e.g., education, age).

Table 2: Descriptive Statistics for Main Variables, Norwegian Monitor Survey

Variable Name	Availability	Observations	Mean (Std.)
<i>Happiness</i>	1985–2013	48,570	0.00 (1.00)
<i>Income Rank</i>	1985–2013	48,570	0.50 (0.29)
<i>Life Satisfaction</i>	1999–2013	29,655	0.00 (1.00)
<i>Perceived Rank</i>	1993–2013	38,938	0.00 (1.00)
<i>Redistribution Preferences</i>	1985–2013	44,480	0.00 (1.00)
<i>Internet Access</i>	1999–2013	29,588	0.87 (0.34)
<i>Internet Rank</i>	1985–2013	48,570	0.50 (0.29)

Notes: See Table 1 for a summary of data definitions for all of the variables listed above. Data from the Norwegian Monitor Survey, which has been collected every second year since 1985.

Table 3: Main Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Happiness	Happiness	Happiness	Happiness	Life Satisf.	Perceived Rank	Redistr. Pref.	Life Satisf.
Income Rank	0.311*** (0.028)	0.316*** (0.040)	0.311*** (0.032)	0.351*** (0.055)	0.585*** (0.056)	2.128*** (0.047)	-0.800*** (0.034)	0.494*** (0.019)
Income Rank * Dummy 2001-2013 ⁽ⁱ⁾	0.090*** (0.032)	0.098* (0.059)	0.090** (0.037)	0.001 (0.067)	0.121** (0.055)	0.228*** (0.047)	-0.107*** (0.039)	0.014 (0.023)
Income Rank * Dummy 2001-2013 * Internet Rank				0.182* (0.110)				
Income Rank * (Year-1985)		-0.001 (0.004)						
Income Rank * Dummy 1997-2000 ⁽ⁱⁱ⁾			0.002 (0.048)			0.069 (0.055)	-0.037 (0.050)	0.023 (0.030)
P-value (i)=(ii)			0.04			0.00	0.11	0.77
Country	Norway	Germany						
Period	85-13	85-13	85-13	85-13	99-13	93-13	85-13	85-13
Observations	48,570	48,570	48,570	48,570	29,655	38,938	44,480	105,738

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Heteroskedasticity-robust standard errors in parenthesis. Each column corresponds to a separate OLS regression. *Happiness*, *Life Satisfaction* and *Perceived Rank* are responses to subjective questions whose responses have been normalized to have mean 0 and standard deviation of 1, and so that higher values denotes higher happiness/satisfaction/rank. *Income Rank* denotes the position of the respondent's household relative to all the other respondents for that year, from 0 to 1. *Dummy 2001-2013* takes the value 1 for 2001-2013. *Dummy 1997-2000* takes the value 1 for 1997-2000. *Internet Rank* corresponds to the position in the national distribution of predicted probability of Internet access in a given year, from 0 (lowest predicted Internet access in the country) to 1 (highest), based on a regression of *Internet Access* on individual characteristics. All regressions include as controls year dummies, age and age squared, one gender dummy, four education dummies, four dummies for marital status, number of working household members and six dummies for household size. Column (4) also includes all the interactive terms from equation (4). Column (8) is based on same regression specification using data for household heads in West Germany from the German Socio-Economic Panel instead. For the rest of the columns, data from the Norwegian Monitor Survey every second year from 1985-2013. See Table 1 for a summary of data definitions and Table 2 for descriptive statistics.

Online Appendix: For Online Publication Only

A Additional Results

A.1 Additional Robustness Checks

Table A.1 and A.2 present some robustness checks. Table A.1 explores the robustness of the results to the use of sampling weights and alternative definitions of income rank. Columns (1) and (2) denote the baseline specifications for happiness and life satisfaction, respectively, which are identical to columns (3) and (5) from Table 3. Columns (3) and (4) from Table A.1 reproduce the same regressions from columns (1) and (2), but using individual-specific sampling weights computed by the team in charge of collecting the survey data. These weights were constructed to match some demographic characteristics (e.g., gender) at the county level. As expected, weighting observations does not change the results: the coefficients in columns (3) and (4) are very similar to (and statistically indistinguishable from) the coefficients from columns (1) and (2).

In the baseline specification, *Income Rank* corresponds to the position of the respondent in the national distribution of household income. An alternative specification consists of the income rank in the local income distribution. First, due to the Balassa-Samuelson effect, the local income rank may predict consumption better than the national income rank. And regarding self-image and social-image, individuals may be judged in comparison to their social contacts, which are drawn disproportionately from the same area of residence. To assess the sensitivity of the results to this specification choice, columns (5) and (6) from Table A.1 reproduce the same regressions from columns (1) and (2) but defining *Income Rank* as the county-rank instead of the national-rank. The results from columns (5) and (6) are similar to (and statistically indistinguishable from) the results from columns (1) and (2). If anything, the effects of the change in disclosure seem larger under the county-rank specification than under the national-rank specification.

Table A.2 explores the robustness of the results to different treatments of the subjective data. As before, columns (1) and (2) denote the baseline specifications for happiness and life satisfaction, respectively, which are identical to columns (3) and (5) from Table 3. Columns (3) and (4) from Table A.2 corresponds to the same specification from columns (1) and (2), with the only difference that the responses to the happiness (life satisfaction) question are coded from 1 to 4 (1 to 5), instead of using the Probit-OLS method and standardization. In terms of signs and statistical significance, the results from columns (3) and (4) are consistent with the results from columns (1) and (2). The coefficients from columns (3) and (4) are

not directly comparable to the coefficients from columns (1) and (2), because of the differences in coding, but can be compared as follows. Column (3) suggests that the change in disclosure increased the happiness-income gradient by 27% (i.e., $\frac{0.049}{0.179}$), which is very close to (and statistically indistinguishable from) the 29% increase implied by the coefficients from column (1). Similarly, column (4) indicates that the change in disclosure increased the life satisfaction-income gradient by 20% (i.e., $\frac{0.088}{0.452}$), which is close to (and statistically indistinguishable from) the 21% increase implied by the coefficients from column (2).

Columns (5) and (6) from Table A.2 estimate the same specifications from columns (1) and (2), except that they use an Ordered Probit model instead of OLS. The results shown in columns (5) and (6) correspond to the raw coefficients from the Ordered Probit model, which are not marginal effects and thus cannot be compared directly to the coefficients from the OLS regressions in columns (1) and (2). In terms of signs and statistical significance, the results from columns (5) and (6) are consistent with the results from columns (1) and (2). In terms of magnitude, column (5) suggests that the change in disclosure increased the happiness-income gradient by 30% (i.e., $\frac{0.113}{0.381}$), which is very close to (and statistically indistinguishable from) the 29% increase implied by the coefficients from column (1). Similarly, column (6) indicates that the change in disclosure increased the life satisfaction-income gradient by 25% (i.e., $\frac{0.165}{0.667}$), which is close to (and statistically indistinguishable from) the 21% increase implied by the coefficients from column (2).

A.2 Effects on the Average Level of Well-Being

In order to estimate the effect of the 2001 change in disclosure on subjective well-being, we propose a differences-in-differences strategy. As discussed in the body of the paper, individuals who do not use Internet may be unaware of the existence of the search tool, and as a result they are arguably less likely to use the search tool to look at the incomes of others and less likely to feel observed by others due to the search tool. Thus, we expect that the change in disclosure affected the well-being of individuals with higher Internet access, but had a smaller effect, and possibly no effect, on individuals with lower Internet access.

Recall from section 4 that $InternetRank_{i,t}$ is the national ranking in predicted Internet access, ranging from 0 (lowest) to 1 (highest). Assume that $InternetRank_{i,t}$ is a measure of the intensity of potential exposure to higher income transparency. Under this assumption, the average effect of income transparency could be identified with the following differences-in-differences specification:

$$SWB_{i,t} = \alpha_1 \cdot InternetRank_{i,t} + \alpha_2 \cdot InternetRank_{i,t} \cdot I_t^{01-13} + X_{i,t}\beta + \delta_t + \epsilon_{i,t} \quad (A.1)$$

As in section 3, $SWB_{i,t}$ is a measure of subjective well-being of individual i in year t , I_t^{01-13} is a dummy variable indicating the period of higher income transparency, $X_{i,t}$ is a vector with a set of control variables, δ_t denotes the year dummies, and $\epsilon_{i,t}$ denotes the error term. The coefficient α_1 estimates the well-being gap between individuals with high and low Internet access during 1985–2000, while α_2 measures the change in that gap from 1985–2000 to 2001–2013. Under the assumption that $InternetRank_{i,t}$ is a valid indicator of potential exposure, then α_2 would measure the potential effect of higher income transparency on average well-being. Of course, this interpretation relies on the additional assumption that that were no other factors that changed in 2001, remained constant until 2013, and affected the well being of individuals differently depending on their Internet access.

Table A.3 shows the regression results. Column (1) reports an estimated α_2 (0.016), the potential effect on average well-being, that is close to zero and statistically insignificant. However, this coefficient is not very precisely estimated, so we cannot reject small or moderate effects: the 90% confidence interval of α_2 ranges from -0.037 to 0.070. Column (2) introduces the falsification test to assess the possibility that the parameter α_2 is biased because of differential pre-trends across individuals with high and low Internet access, as in the specification from equation (3) in section 3. The results from column (2) suggests that differential pre-trends are not a source of concern: the coefficient α_2 is still small and statistically insignificant, and the coefficient on the interaction with *Dummy 1997–2000* is also small and statistically insignificant. Column (3) reproduces the analysis using a measure of actual Internet access instead of *Internet Rank*. The disadvantage of this method is that the Internet access question was introduced for the first time in 1999, leaving us with only one year of pre-treatment data. Column (3) reports an estimated α_2 of -0.016, which is also close to zero and statistically insignificant. Note that, unlike in the triple-differences specification, there is no substantial loss in precision from using the raw *Internet access* instead of *Internet Rank*. Column (4) uses life satisfaction instead of happiness as dependent variable. Again, the estimated α_2 (0.023) is close to zero and statistically insignificant. In summary, the evidence suggests that the change in disclosure had an insignificant effect on average well-being.

Columns (5) and (6) from Table A.3 reproduce the analysis of the average effects on the other outcomes reported in the body of the paper. Column (5) shows that the estimated average effect on *Perceived Rank* (0.018) is close to zero and statistically insignificant. In turn, this evidence suggests that, on average, perceptions about the income rank were unbiased. Consistent with the effect on *Perceived Rank*, column (6) shows that the estimated average effect on *Redistribution Preferences* (-0.008) is also close to zero and statistically insignificant.

Table A.1: Additional Robustness Checks: Weighting, and Definition of Income Rank

	(1)	(2)	(3)	(4)	(5)	(6)
		Life		Life		Life
	Happiness	Satisf.	Happiness	Satisf.	Happiness	Satisf.
Income Rank	0.311*** (0.032)	0.585*** (0.056)	0.306*** (0.036)	0.564*** (0.063)	0.269*** (0.032)	0.555*** (0.056)
Income Rank * Dummy 2001-2013 ⁽ⁱ⁾	0.090** (0.037)	0.121** (0.055)	0.088** (0.043)	0.111* (0.061)	0.098*** (0.037)	0.113** (0.055)
Income Rank * Dummy 1997-2000 ⁽ⁱⁱ⁾	0.002 (0.048)		-0.021 (0.056)		0.006 (0.048)	
P-value (i)=(ii)	0.04		0.03		0.04	
Weights	No	No	Yes	Yes	No	No
Income Rank	Nation	Nation	Nation	Nation	County	County
Period	85-13	99-13	85-13	99-13	85-13	99-13
Observations	48,570	29,655	48,570	29,655	48,570	29,655

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Heteroskedasticity-robust standard errors in parenthesis. Each column corresponds to a separate OLS regression. *Happiness* and *Life Satisfaction* are responses to subjective questions where higher value denotes higher happiness/satisfaction, normalized to have mean 0 and standard deviation of 1. *Income Rank* denotes the position of the respondent's household, from 0 to 1, relative to all the other respondents for that year in the nation (columns (1) to (4)) or county (columns (5) and (6)). *Dummy 2001–2013* takes the value 1 for 2001–2013. *Dummy 1997–2000* takes the value 1 for 1997–2000. In columns (3) and (4), the regressions use population weights computed by the group in charge of conducting the survey. All regressions include as controls year dummies, age and age squared, one gender dummy, four education dummies, four dummies for marital status, number of working household members and six dummies for household size. Data from the Norwegian Monitor Survey, which has been collected every second year since 1985. See Table 1 for a summary of data definitions and Table 2 for descriptive statistics.

Table A.2: Additional Robustness Checks: Coding of Subjective Data and Ordered Probit

	(1)	(2)	(3)	(4)	(5)	(6)
	Happiness	Life Satisf.	Happiness	Life Satisf.	Happiness	Life Satisf.
Income Rank	0.311*** (0.032)	0.585*** (0.056)	0.179*** (0.018)	0.452*** (0.043)	0.381*** (0.039)	0.667*** (0.064)
Income Rank * Dummy 2001-2013 ⁽ⁱ⁾	0.090** (0.037)	0.121** (0.055)	0.049** (0.021)	0.088** (0.042)	0.113** (0.045)	0.165*** (0.062)
Income Rank * Dummy 1997-2000 ⁽ⁱⁱ⁾	0.002 (0.048)		0.001 (0.028)		0.000 (0.059)	
P-value (i)=(ii)	0.04		0.05		0.03	
Model	OLS	OLS	OLS	OLS	O-Probit	O-Probit
POLS Transformation	Yes	Yes	No	No	No	No
Period	85-13	99-13	85-13	99-13	85-13	99-13
Observations	48,570	29,655	48,570	29,655	48,570	29,655

Notes: *** p<0.01, ** p<0.05, * p<0.1. Heteroskedasticity-robust standard errors in parenthesis. Each column from (1) to (4) corresponds to a separate OLS regression, while each of columns (5) and (6) corresponds to raw coefficients from an Ordered Probit model. *Happiness* and *Life Satisfaction* are responses to subjective questions where higher value denotes higher happiness/satisfaction. In columns (1) and (2), responses to these questions were coded using the Probit-OLS method, and then normalized to have mean 0 and standard deviation of 1. In columns (3) and (5), responses to the happiness question are assigned values from 1 (not at all happy) to 4 (very happy). In columns (4) and (6), responses to the life satisfaction question are assigned values from 1 (very dissatisfied) to 4 (very satisfied). *Income Rank* denotes the position of the respondent's household relative to all the other respondents in the Nation or County for that year (from 0 to 1). *Dummy 2001-2013* takes the value 1 for 2001-2013. *Dummy 1997-2000* takes the value 1 for 1997-2000. All regressions include as controls year dummies, age and age squared, one gender dummy, four education dummies, four dummies for marital status, number of working household members and six dummies for household size. Data from the Norwegian Monitor Survey, which has been collected every second year since 1985. See Table 1 for a summary of data definitions and Table 2 for descriptive statistics.

Table A.3: Additional Regression Results: Effects on the Average Level of Well-Being

	(1)	(2)	(3)	(4)	(5)	(6)
	Happiness	Happiness	Happiness	Life Satisf.	Perceived Rank	Redistr. Pref.
Internet Rank	0.079 (0.051)	0.090 (0.056)				
Internet Rank * Dummy 2001-2013	0.016 (0.033)	0.008 (0.038)				
Internet Rank * Dummy 1997-2000		-0.022 (0.047)				
Internet Access			0.011 (0.036)	0.011 (0.035)	0.027 (0.031)	-0.010 (0.035)
Internet Access * Dummy 2001-2013			-0.016 (0.041)	0.023 (0.039)	0.018 (0.036)	-0.008 (0.039)
Period	85-13	85-13	99-13	99-13	99-13	99-13
Observations	48,570	48,570	29,588	29,459	29,560	27,215

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Heteroskedasticity-robust standard errors in parenthesis. Each column corresponds to a separate OLS regression. *Happiness*, *Life Satisfaction*, *Perceived Rank* and *Redistribution Preferences* are responses to subjective questions that have been normalized to have mean 0 and standard deviation of 1, and so that a higher value denotes higher happiness/satisfaction/rank/redistribution. *Internet Access* is a dummy variable that takes the value 1 if the individual has Internet access in at least one of the following: home, work, school, university or elsewhere. *Internet Rank* corresponds to the position in the national distribution of predicted probability of *Internet access* in a given year, from 0 (lowest predicted Internet access in the country) to 1 (highest), based on a regression of *Internet Access* on individual characteristics. *Dummy 2001–2013* takes the value 1 for 2001–2013. *Dummy 1997–2000* takes the value 1 for 1997–2000. All regressions include as controls year dummies, age and age squared, one gender dummy, four education dummies, four dummies for marital status, number of working household members, six dummies for household size and *Income Rank* (i.e., the respondent’s position in the national distribution of household income for that year). Data from the Norwegian Monitor Survey, which has been collected every second year since 1985. See Table 1 for a summary of data definitions and Table 2 for descriptive statistics.

Table A.4: Auxiliary Regression Results: Predictors of Internet Access

Dependent Variable: <i>Internet Access</i> * 100			
Female	-4.66*** (1.03)	No. of HH Members (omitted: 1) 2	4.24** (2.13)
Age	0.95*** (0.22)	3	2.19 (2.23)
Age Squared	-0.02*** (0.00)	4	2.24 (2.44)
Education (omitted: Primary School)			
Junior School	18.46*** (3.13)	5+	2.46 (2.66)
High School	27.74*** (2.91)	No. of HH Workers (omitted: 0) 1	16.54*** (2.73)
College	39.20*** (2.87)	2	21.19*** (2.78)
Marital Status (omitted: Married)			
Cohabitant	-5.92*** (1.64)	3+	26.83*** (3.23)
Unmarried / Never Married	0.08 (2.37)	Constant	33.86*** (6.26)
Separated / Divorced	1.63 (2.45)		
Widow / Widower	-1.86 (3.86)		

Notes: $N = 3,931$. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Heteroskedasticity-robust standard errors in parenthesis. The dependent variable, *Internet Access*, is a dummy variable that takes the value 1 if the individual responds affirmatively to at least one of the following questions: “Do you have Internet access at home? Do you have Internet access at work? Do you have Internet access at your school or university? Do you have Internet access elsewhere?” Coefficients from an OLS regression using responses from 2001. Data from the Norwegian Monitor Survey. The average of the outcome variable is 79.32 percent, and the R^2 is 0.37.

B Further Details about the Disclosure Policy

B.1 Recent History of Changes in Regulation of Disclosure

In 2004, the new government officials banned the “direct” publication of search records by the press. Only the tax agency was allowed to publish the raw data, which was only available for a three-week period following the release of the data in mid-October. That is, individuals could do all the searches that they were used to make before, but they could only make them during a three-week period and from an official website. The restriction that individuals had to use the official website was not significant, not only because the tax agency website was equally easy to use, but more importantly because the newspapers easily bypassed this limitation by building their own search interface on top of the tax agency’s interface (see for example Figure B.4). The websites also made an agreement with the government that they would receive the raw data but, outside of the three week period, were only allowed to publish records for the top income earners in each local area (Teknologiradet, 2010). The three-week restriction was probably the most significant restriction on the income transparency since 2001, but it may have meant that individuals were doing the same number of searches that they used to do during the year, only that now more concentrated – indeed, as shown in section 2, individuals did a lot of the searches in that three-week period anyway. Only one year of our data corresponds to this period of limitations, the fall of 2005. In 2007, all of these restrictions were lifted by the new government officials. Thus, in the fall of 2007 the tax data was at least as easily accessible as in the fall of 2001.

A restriction was introduced again in 2011: individuals had to use the official website of the tax agency to conduct the searches. This time, however, the search tool was available the entire year, not just for three weeks. Also, this time the individual must log-in to the tax agency website to access the search tool, which meant that newspapers could no longer build their own search tools piggybacking on the tax agency website. The log-in required a pin-code and a password, which the users presumably knew already since this is the same log-in that they use for a variety of tax purposes. The 2011 legislation also introduced a limit on the maximum number of searches per month (500), although it seems that such restriction would not be binding for the vast majority of individuals. In spite of being more significant, these restrictions were not a big barrier. As reported by Norway’s Ministry of Finance (2014), 920,896 users conducted over 17 million searches in 2013.

The last restriction was introduced in 2014, when the government decided that the searches would no longer be anonymous: any individual could use the same website to find out who was searching for their tax records. Consistent with the expectations of the authorities, it was reported that the number of searches dropped by 88% from 2013 to 2014. The

share of users logging in to the system did not decrease by much, but instead of searching for others, a majority of users used the website to look at the list of individuals who had searched for their information.⁴⁰

B.2 Snapshots of the Search Tools and Search Results

All the major newspapers had their own website with search tools to browse the tax records: e.g., www.skattelister.no, www.nrk.no/skatt, www.tu.no/skattelister, skatt.na24.no. Figures B.1-B.4 show snapshots of some of these websites – since most of these websites are no longer online, snapshots of the websites were obtained from the Internet Archive (web.archive.org). Figure B.1 corresponds to the first newspaper to make the data available back in the fall of 2001. This snapshot corresponds to the home page as of 2010. Note on the top-right corner an advertisement for the smartphone application provided by the newspaper, featuring the option to connect to Facebook. Figure B.2 corresponds to the advanced search tool in another website as of 2009. Note in the top-right corner the option to search by postal code. Figure B.3 corresponds to one of the few websites that is still functional as of August 1, 2015, which offers data from the 2008 tax records. The snapshot corresponds a sample profile, listing first and last name, age, city, net income, net worth and taxes. Last, Figure B.4 shows one of the websites during the “restriction” in 2004–2006 that the searches could only be conducted from the official website. These websites bypassed the limitation by simply building their own search interface on top of the tax agency’s interface: please note in the snapshot that the bottom half of the website is actually coming from the official website of the tax agency (“Skatteetaten,” which translates to “Tax Administration”).

⁴⁰Source: “«Ingen» sjekker skattelisterne lenger – frykter å bli uthengt som snokere,” NRK, October 28, 2014. Interestingly, some individuals started selling a search service under their names to allow users make anonymous searches (Source: “Christina sjekker skattelisterne for deg,” Bergens Tidende, October 17, 2014).

Figure B.1: Search Tool in skattelister.no as of June 16, 2010 (Source: web.archive.org)

Figure B.2: Search Tool in nrk.no/skatt as of March 31, 2009 (Source: web.archive.org)

Figure B.3: Sample Profile in skatt.na24.no as of August 1, 2015

NA24
Næringslivsavisen på nettet

Propaganda | Priv.øk. | Bolig | Aksjekurser | Fondskurser | Valutakurser | Bloggere | Finansordboken

Vær | MittOppdrag | Dating | Børs og valuta | Blogglisten | Hjerneklubben | Bileier | Odds | Trav | Momondo | Auksjon | Skattesøk | 007

Skattesøk på John Alieu Carew

Fornavn:	John Alieu
Etternavn:	Carew
Alder:	36
Sted:	Oslo
Inntekt:	334.012
Formue:	5.402.358
Skatt:	190.924

Figure B.4: Search Tool in nrk.no/skatt as of February 7, 2006 (Source: web.archive.org)

NRK.NO NYHETER ØKONOMI OM NRK MEDLEM MOBIL BUTIKK TEKST-TV BARN NRK P3

Skattelister 2004

Årskavalkade 2005

SØK NRK NETTRADIO NRK NETT-TV

Her er du: NRK.no > Nyheter > Økonomi > Skattelister > Skattelister 2004

Sist oppdatert 00:00

Skatteetaten

Skattelista 2005 for personer

Fornavn* ?

Etternavn* ?

Jeg er usikker på hvordan navnene staves

Poststed* ?
Land hvis bosted i utlandet [Poststedsversikt ?](#)

Alder (+/- 5 år) ?

Kode* ?
Skriv inn tegnene du ser i bildet under. [Hvorfor?](#)

Felt med * er obligatoriske

Søk

[Slik søker du](#)

[Spørsmål og svar](#)

[Regler for publisering av skattelistene](#)

[Om personvern](#)

[Skattelista for selskaper](#)

[Tøm alle felt](#)

C A Simple Model of the Effects of Income Transparency Through Self-Image and Social-Image

This Appendix provides a simple model to show that, due to self-image and social-image, an increase in income transparency can increase the gradient between utility and income rank. Additionally, this model provides a framework for the back-of-the-envelope calculations of the value of self-image and social-image.

There is a continuum of agents with a non-degenerate income distribution, where r^{true} denotes the true relative position in the income distribution of a given agent. Agents compete for self-esteem and social-esteem in interactions with other agents from the same population. In each of these interactions, the incomes of the agents involved in the interaction happen to be observable with some exogenous probability $\nu \in [0, 1]$. This parameter ν is a reduced-form representation of the degree of income visibility. Note that a more realistic model would have two ν 's, one relevant for the formation of self-image and another for the formation of social-image, but we use a unique ν to simplify the notation. For example, it is probably easier to observe information to infer one's position in the income distribution, for which it suffices to have access to aggregate income statistics, than to observe the income of a particular individual.

Intrinsic Utility. We assume that intrinsic utility from income is a linear function of the true income rank of the individual:

$$U^{intrinsic} = \eta_0 \cdot r^{true} \tag{C.1}$$

Note that intrinsic utility depends on absolute income, because r^{true} is a monotone transformation of absolute income (i.e., just like the logarithm of absolute income).

Social-Image Utility. The agent is paired with a random agent from the population. A third agent wants to provide a non-market good, social esteem, to the individual in the pair with the higher income. With probability ν , the third agent can observe the incomes of the two agents, in which case he always gives the non-market good to the agent with the higher income. With probability $1 - \nu$ the third agent cannot observe incomes, in which case he simply randomizes which agent gets the non-market good. The utility of obtaining the non-market good is given by $\eta_1 > 0$. As a result, the ex-ante expected social-image utility is:

$$U^{social} = \nu \cdot r^{true} \cdot \eta_1 + (1 - \nu) \cdot \frac{1}{2} \cdot \eta_1 \tag{C.2}$$

By taking the derivative of (C.2) with respect to r^{true} , we obtain the gradient between social-image utility and income. By taking an additional derivative with respect to ν , it turns

out that this gradient increases with income visibility:

$$\frac{\partial^2 U^{social}}{\partial r^{true} \partial \nu} = \eta_1 > 0 \quad (\text{C.3})$$

Intuitively, increasing visibility would make an individual with below-median income worse off, because with a higher probability her peers would observe her income and learn that she is poorer than they would have thought otherwise. On the other hand, increasing visibility would make an individual with above-median income better off, because with a higher probability the peers would observe her income and learn that she is richer than they would have thought otherwise.

Self-Image Utility. The agent is paired with another agent randomly chosen from the population. The agent must decide whether to award another non-market good, self-esteem, to herself or not. That is, instead of being judged by an objective third agent, like in social-esteem, the self-esteem is assigned by oneself. This non-market good brings utility $\eta_2 > 0$. The agent assigns this non-market good to herself with probability equal to her probability belief that her income is higher than the income of her randomly-assigned peer. With probability ν , she can observe the actual income of the peer, in which case she gets the good if and only if her income is actually higher than the income of the peer (which, from an ex-ante perspective, happens on expectation with probability r^{true}). With probability $1 - \nu$, the income of the peer is not observable, in which case whether she gets the non-market good or not will depend entirely on her prior belief about her position in the income distribution. Let r^{self} be this prior belief. We let the prior beliefs be heterogeneous, but we make the following assumption about the joint distribution of actual income ranks and prior beliefs about income ranks: $E[r_{prior}^{self} | r^{true}] = \theta_0 + \theta_1 \cdot r^{true}$.

The most realistic case would be $\theta_1 = 0$: i.e., if all incomes are truly unobservable, then self-perceptions about income rank should be orthogonal to actual income ranks. However, we allow for a more general case. The case $\theta_1 < 1$ would mean that poor individuals systematically over-estimate their position in the income distribution while rich individuals under-estimate their position, as documented in Cruces, Perez-Truglia and Tetaz (2013). We also allow for the possibility that $\theta_1 > 1$: poor individuals think they are poorer than they actually are, and rich individuals think that they are richer than they actually are. As a result, the ex-ante expected utility from self-image is:

$$U^{self} = \nu \cdot r^{true} \cdot \eta_2 + (1 - \nu) \cdot (\theta_0 + \theta_1 \cdot r^{true}) \cdot \eta_2 \quad (\text{C.4})$$

By taking the derivative of (C.4) with respect to r^{true} , we obtain the gradient between self-image utility and income. By taking an additional derivative with respect to ν , we can

see how this gradient changes with income visibility:

$$\frac{\partial^2 U^{self}}{\partial r^{true} \partial \nu} = \eta_2 \cdot (1 - \theta_1) \quad (\text{C.5})$$

If $\theta_1 < 1$, as documented in Cruces, Perez-Truglia and Tetaz (2013), then the increase in income visibility will increase the gradient between utility and true income rank. Intuitively, when incomes are more easily observable then poor individuals learn that they are actually poorer than they thought, thus losing self-image utility. And rich individuals learn that they are actually richer than they thought, thus gaining self-image utility. However, if $\theta_1 > 1$ then the opposite result could hold: the increase in income visibility would reduce the gradient between utility and true income rank. In practice, to figure out whether $\theta_1 < 1$ or $\theta_1 > 1$, we can test the following intermediate prediction. Let r_{post}^{self} be the posterior belief about own income rank, and consider the following conditional expectation:

$$E \left[r_{post}^{self} | r^{true} \right] = \nu \cdot r^{true} \cdot \eta_2 + (1 - \nu) \cdot \theta \cdot r^{true} \quad (\text{C.6})$$

The income visibility has the following effect on the gradient between the posterior belief and r^{true} :

$$\frac{\partial^2 E \left[r_{post}^{self} | r^{true} \right]}{\partial r^{true} \partial \nu} = (1 - \theta_1) \quad (\text{C.7})$$

Thus, if $\theta < 1$, we would predict that higher income visibility increases the gradient between self-perceived income rank and actual income rank. This is a prediction that we test (and confirm) with the survey data.

For the back-of-the-envelope calculations, we focus on the case $\theta_1 = 0$, which we believe makes the most sense. Adding up the three terms of the utility function, (C.1), (C.2) and (C.4), and re-arranging:

$$U = (\beta_1 + \beta_2 \cdot \nu) \cdot r^{true} + \epsilon, \quad (\text{C.8})$$

with $\beta_1 = \eta_0$, $\beta_2 = \eta_1 + \eta_2$ and $\epsilon = (1 - \nu) \cdot \left(\frac{1}{2} \cdot \eta_1 + \theta_0 \cdot \eta_2 \right)$

Note that β_1 measures the intrinsic utility from income, while $\beta_2 \cdot \nu$ measures the utility from income through self-image and social-image. As a result, $\frac{\beta_2 \cdot \nu}{\beta_1 + \beta_2 \cdot \nu}$ measures the value of income comparisons relative to intrinsic consumption. We employ this formula for back-of-the-envelope calculations in section 5.

Finally, we can also explore the predictions of this model for the effect of income transparency on average well-being. Regarding social-image, it is straightforward to check that

the average effect is zero. Intuitively, increasing visibility transfers social-esteem from poor to rich individuals, but no social-esteem gets created or destroyed in the process. Regarding self-image, it is straightforward to check that the average effect of higher visibility depends on whether θ_0 is above or below $\frac{1}{2}$. Intuitively, if $\theta_0 > \frac{1}{2}$, it means that on average individuals were over-estimating their own position in the income distribution. Since the higher transparency corrects this systematic bias, there is a net loss in utility from self-esteem. Similarly, if $\theta_0 < \frac{1}{2}$, higher visibility would lead to an increase in average happiness; and if the average bias in self-perceived income rank was zero ($\theta_0 = \frac{1}{2}$), then higher income transparency would have no effect on the average utility from self-image.