Household level heterogeneity in the income elasticities of demand for international leisure travel

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Abstract
This article deepens the understanding of household level heterogeneity of income elasticities of demand for international leisure travel. This is done through the use of Swedish household level expenditure data which together with censored quantile regression allows for estimation of income elasticities based on relative consumption levels. In addition, an analysis of how the distribution of income elasticities was affected by the 2008 financial crisis is made. Results show a great heterogeneity in the estimated income elasticities, with income elasticities being the largest for the households who consume relatively little of the good, and a small positive effect of the financial crisis on the estimated distribution of income elasticities. These results can be used by policy makers, as well as managers in the tourism industry, to predict and influence the demand of international tourism at a more detailed level. The results also go in line with theoretical predictions and give further insight in market penetration as well as an ongoing structural change in the demand for international tourism.

Keywords
censored quantile regression, heterogeneous elasticities, income elasticity, international leisure travel, international tourism

Introduction
Income has been shown to be one of the most important determinants of international tourism demand in a multitude of papers. While there exists a general consensus in the literature that international tourism is a luxury good with an income elasticity above one, meta-studies such as Crouch (1996) and Peng et al. (2015) show that there is a large variation in the estimates between papers, some even showing negative income elasticities. One explanation for this observed range in estimates is that different approaches are used to estimate the income elasticity. A clear difference

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that can be observed in the literature is which type of data that is used in the estimation. Historically, most papers have used aggregate data on a country or route level, where some version of GDP is the most common income variable and the number of passengers is the most common measure for tourism demand (see, for example, Crouch, 1996). While these types of income elasticity estimates are useful for many applications, such as forecasting of international passenger flows, the use of micro-econometric models have several advantages as it more closely reflects the behavior of the tourists. Papers using aggregate data are still the most common approach in the literature, but the use of micro-data has become a lot more common in the past decades (Wang and Davidsson, 2010). Most of these papers use data that are collected on location however, and while this is helpful for the local tourism industry, the external validity of the estimates is lower due to self-selection by tourists to the destination that is being considered. In addition, the bias that comes from the fact that not everyone in a given country travels abroad in a given time period cannot be addressed. As is pointed out by, for example, Brida and Scuderi (2013), the analysis is usually also severely hampered by the fact that these types of on-location surveys rarely have detailed income data as this variable is usually collected as a categorical rather than a continuous variable due to anonymity reasons, and the knowledge on the income elasticities that they provide are thereby a bit limited.

One way to solve these issues is to use micro-econometric methods when analyzing a representative country level sample, which combines the advantages of using micro-data with the generalizability to a country level that estimations using aggregate data provide. In particular, the use of this type of data enables the researcher to address heterogeneity at a household level that can be analyzed for the entire population, as issues due to self-selection and censoring can be addressed. Despite these advantages, there are so far relatively few papers that analyze income elasticities using representative household data, Alegre and Pou (2004), Hung et al. (2012) and Alegre and Pou (2016) being three examples, and it is clear that further research using this type of data is useful to deepen the understanding of income elasticities for the demand of international tourism at a household level.

Heterogeneity is also a key explanation for the variability in estimated income elasticities that is observed in the meta-studies. Historically, the income elasticity has been assumed to be constant in tourism modeling but newer empirical evidence suggests that the income elasticity varies due to a number of factors such as the relative income level in the source country (Waqas-Awan et al., 2020), type of destination that is considered (Peng et al., 2015) or the time period that is being studied (Gunter and Smeral, 2016). Despite the fact that an understanding of this variability is important in, for example, forecasting performance, as shown by, for example, Smeral (2017), little attention has so far been shown to the heterogeneity in income elasticities at a household level. In addition to the previously mentioned advantages of household level estimation, an understanding of household level heterogeneity can help improve managerial decisions in the tourism industry as well as policy measures considered since aggregate income elasticity phenomena, such as differences between countries or decreasing elasticities over time, can be better understood.

This article tries to fill this research gap in two ways. First, we estimate heterogeneous income elasticities for households that have different levels of demand for outbound international leisure travel using Swedish household level expenditure data and censored quantile regression (CQR). Different income elasticities are estimated for each percentile of the conditional distribution of tourism expenditure so that the effect of a change in household income for relative top, mid and low spenders is analyzed separately. This addresses both household level heterogeneity at the same time as the advantages of using a representative country level sample are utilized. The resulting heterogeneity and its implications are analyzed using intuition from the theoretical contributions of Matsuyama (2002) and Morley (1998), who both predict varying income elasticities based on
income and expenditure levels. Second, we use the financial crisis of 2008 to estimate how the distribution of income elasticities changes at a household level in response to an economic crisis.

The main purpose of investigating household heterogeneity along the expenditure distribution is threefold. First of all, heterogeneous income elasticities at a household level give a better insight into how economic policy will affect household demand for international tourism. This insight can be used from a governmental perspective, when wanting to increase or decrease demand for international tourism, as well as managers in the tourism industry. The latter is especially true as customers’ expenditure levels, in comparison to, for example, customers’ income, is observable by travel agencies, hotels and other actors in the tourism industry. Second, this type of heterogeneity analysis can be used to determine the level of market penetration and saturation for outbound international tourism in the country that is being studied, in this case Sweden. In general, aggregate income elasticities are used to determine the level of market maturity, a lower income elasticity signifying a higher level of maturity (see, for example, Graham, 2000). Getting an understanding of household heterogeneity in income elasticities gives a more nuanced picture of how far households have reached in consuming international tourism to satiety, at the same time as it provides further insight in structural change in demand for tourism and its effect on long term income elasticities. Third, a distributional understanding of how a financial crisis affects household level income elasticities improves the understanding of how resilient households’ income elasticities are to economic crisis. This is important to be able to predict how fast the demand for international tourism will recover after an economic crisis, and to understand which type of households that will be the main driver of this recovery.

The main contribution of this article is therefore that heterogeneity based on household level demand for international tourism is considered, a metric that in comparison to household income is directly observable by actors in the tourism industry. While a few papers studying heterogeneity along the income distribution are already available (such as Alegre and Pou, 2004, and Alegre et al., 2013), only one other paper that use a representative household sample looks at heterogeneity along the tourism expenditure distribution (Hung et al., 2012). As already explained, this is valuable for both the tourism industry directly as well as policy makers. The second contribution is that the distributional effect of the 2008 financial crisis is estimated, something that to the best of our knowledge has not been previously considered in the literature. This is especially useful since we are currently in the midst of an economic crisis due to the COVID-19 pandemic, and while the current crisis in the tourism market is a lot different from the dip in demand because of the 2008 financial crisis, households’ responsivity to increasing incomes will likely still be an important factor in the recovery of international tourism demand. In addition, due to the rich Swedish data that are used, a few other minor contributions can be made. Estimations are made for only international tourism expenditure, not all types of tourism as is usually the case in the household level literature. This distinction is relevant as domestic and international tourism differs in terms of income elasticities. In addition, separate estimations for expenditures made to booking agencies before departure and expenditures that are made on location are carried out. Differences in income elasticities when current income or total expenditure is used as the income variable are also considered, a choice that is often discussed in the literature (see, for example, Alegre and Pou, 2016).

The rest of the article is structured as follows. In the next section, the relevant literature on household heterogeneity in income elasticities as well as a brief empirical background on international travel from Sweden is presented. In the Data section, the data that are used and how the key variables are constructed are presented. In the Econometric Strategy section, the econometric strategy with the CQR estimator is presented. In the Main Results section, the results are presented and discussed together with robustness checks of the estimates. The Conclusion section concludes.
Literature review and empirical background

The empirical literature on household heterogeneity of the income elasticity of demand is still rather sparse, but it is clear that there exists heterogeneity along several dimensions. The main source of heterogeneity that is considered is differences in income elasticities depending on the level of household income. The pattern of heterogeneity along the income distribution appears to be different depending on whether the income elasticity of tourism participation or tourism expenditure is considered. For the probability of tourism participation, Alegre and Pou (2004) and Alegre and Pou (2016) find decreasing income elasticities for Spanish households as income increases. Alegre and Pou (2004) estimate the income elasticity of probability of tourism participation to be around 0.9 for the poorest households, decreasing to 0.6 for the richest households. Higher education also leads to a lower income elasticity for all percentiles of the income distribution. Alegre and Pou (2016) find different elasticity levels depending on what type of income measure they use, current income or total expenditure, with the former generating elasticity estimates between 0.3 and 0.17 and the latter estimates between 1.2 and 0.3. Eugenio-Martin and Campos-Soria (2011) also estimate heterogeneous income elasticities of the probability of participation in tourism using a household survey for EU-15 countries. They find that the income elasticity of probability of participation in domestic travel decreases from around zero for the lowest income decile, to negative 5 for the highest income decile, while the income elasticity for the probability of participation in international travel increases from 0 to around 1 for the first income deciles, after which it decreases back to around 0 for the highest income deciles. The income elasticity of tourism participation therefore seems to be in general decreasing in income. When it comes to the income elasticity of tourism expenditure, rather than probability of participation, Alegre et al. (2013) estimates heterogeneous elasticities, once again with Spanish household data, and find that the income elasticity increases with income from around 1.3 to 1.9 over the income distribution.

When it comes to household heterogeneity based on the size of tourist expenditure, most studies that address this are made with data that are collected on location. Marrocu et al. (2015) is one example who analyzes heterogeneity of micro-determinants of tourism expenditure in Sardinia using quantile regression. As their income variable is categorical, they do not estimate income elasticities directly, but they show that high income households spend more than low income households and that this difference increases over the expenditure distribution. Pérez-Rodríguez and Ledesma-Rodríguez (2019) is another example that look at heterogeneity in tourism expenditure on the Canary Islands. They also use three levels of income in their analysis and find similar results for the effect of income along the expenditure distribution as Marrocu et al. (2015). An example of paper that uses visitor survey data with detailed income information is Chen and Chang (2012). They focus on the effect of travel-agents on travel expenditure, but use quantile regression to estimate the effects of interest at five different quantiles. They find a quite low heterogeneity in income effects as the income estimates are stable over most quantiles, but the top quantile (90th) shows an income effect that is roughly four times higher than the other considered quantiles. The only paper that does a heterogeneous analysis of tourism expenditure using a representative household sample is, to the best of our knowledge, Hung et al. (2012) who use the Survey of Family Income and Expenditure in Taiwan. Their dependent variable is percentage of household income spent on tourism, and using quantile regression they find negative income effects for lower quantiles (10th and 25th) and positive effects for the 50th quantile and above.

The effects of economic crises on the income elasticity of tourism demand are also under-researched, especially at a household level. As shown by, for example, Smeral (2014), this is also a very important aspect to consider to improve forecasting performance, especially when forecasting
is made in the midst of economic turbulence. Interestingly, differences in income elasticities before
and after an economic crisis are found in the papers that do estimations based on aggregate data, and
the direction of the effect can also go both ways depending on which origin country is being studied,
but the same effects are not found in the two papers that use household data in their estimations.
Smeral (2014), for example, find that Australia and Japan have higher income elasticities in slow
growth, post-crisis, periods than fast growth periods (4.91 vs. 2.95 for Australia and 3.97 vs. 2.17 for
Japan) while the EU-15 countries and USA have higher income elasticities in fast growth periods
than slow growth (2.43 vs. 1.28 for EU-15 and 2.37 vs. 1.17 for USA). Gunter and Smeral (2017)
similarly find that income elasticity of outbound tourism in the period after the financial crisis (year
2008–2014) is significantly higher (1.64) than in the fast growth period preceding the crisis (0.65).
At a household level, only two papers have been written where the effect of the financial crisis on the
income elasticity of tourism is tested. The first one is Alegre et al. (2013) that use Spanish
Household data for the period 2006–2010. They find very small effects on the income elasticity of
both the probability of participation and on tourism expenditure conditional on participation, but in
different directions. The income elasticity for participation decreases slightly (from 0.57 to 0.51)
while the elasticity for expenditure conditional on participation increases slightly (0.61–0.77) and
even though the differences are significant, the change due to the crisis is far from those estimated
using aggregate data. Alegre and Pou (2016) use the US Household Expenditure Survey to estimate
the effect of the crisis, and find no significant effect on the income elasticity when the periods 2005–
2008 and 2009–2012 are compared. These contradicting results are by themselves interesting, and
motivate further research in the area, especially at a household level as the present article considers.
In addition, none of the papers that considers the effect of the crisis on a household level estimates
distributional effects of the crisis. While they consider heterogeneity for the full sample, as pre-
viously explained, they do not estimate separate effects of the crisis for different types of
households. This is potentially important, especially if the crisis has heterogeneous effects on the
income elasticity. In theory, the average income elasticity could be unchanged while the distribution
is affected, increases for some households being canceled by decreases for others, which would
affect both forecasts and policy recommendations.

From a theoretical point of view, household heterogeneity of income elasticities is expected for a
luxury good such as international tourism. According to Engel’s law (Engel, 1857), households that
get richer reduce their expenditure share on necessities such as food in favor of more luxurious
goods. However, what is considered a necessity and a luxury changes as a society keeps getting
richer; something that was considered the highest of luxury 100 years ago, such as car ownership, is
now considered to be a necessity by many households. Matsuyama (2002) builds on this premise
and constructs a model with a spectrum of goods that are introduced to and consumed by agents in
sequence: each new good is consumed up to a certain level after which more income is used to
consume the next affordable item on the agents’ shopping list of preferred goods. As households
differ in income, each good starts off as a luxury good that only the richest households can afford. As
income levels rise, each new good goes from being a luxury to a necessity that everyone consumes.
Increased demand for the good also increases the efficiency of its production which leads to a
decrease in price of the good. This price reduction in turn leads to the richest households having
money left over to consume the next good, and the cycle continues. If this theory is relevant to
international tourism, we expect different households to have different income elasticities for the
good at the same time: the richest households who consume the good to satiety will have the lowest
income elasticity, the good is now a necessity for these households, and the poorest households, for
which the good is the highest luxury, who can only consume little of the good will have the highest
income elasticity. While income is the main driver behind this heterogeneity, it is also implied that
income elasticities falls as the level of consumption of the good increases. In addition to heterogeneity between households at a cross-section, this theoretical set-up also provides intuition for how income elasticities can change at an aggregate level for luxury goods: as the good becomes more and more affordable, the income elasticity will decline as more and more households perceive the good as a necessity rather than a luxury good.

Differences in income elasticities for international tourism based on differences in income levels is also hypothesized by Morley (1998), who develops a dynamic model that allows demand elasticities to vary over time. He hypothesizes a U-shape curve of income elasticities: the richest and poorest countries are expected to have the lowest income elasticity while the mid-income countries are expected to be the most responsive to an increase in income. The poor having a low response as they still only barely can afford to travel internationally, and an increase in income must be allocated toward other more important goods first, and the rich countries having a low elasticity as they already consume international tourism until satiety (that is the good is no longer a luxury good in these countries). The middle income countries can afford to travel internationally but are not consuming the good to satiety, and an increase in income will be allocated to this good to a large degree. While Morley (1998) constructed this hypothesis with a country comparison in mind, it is reasonable that a similar pattern is present also at a household level within a country. This has already been investigated along the income distribution to some extent, as already described, but a similar pattern can be expected also along the expenditure distribution, with the exception that those who consume nothing of the good has a zero income elasticity.

Turning now to a descriptive empirical background of the international travel from Sweden, the main dependent variable in this article is expenditure on international leisure travel. This expenditure category mainly consists of expenditure on international air travel and hotel payments. It is therefore useful to examine key background information on the development of the consumption and prices for these goods, as well as the development of income levels in Sweden.

International air travel, the main mode of transportation for Swedish travelers going abroad, has been continuously increasing in Sweden over recent decades, both in absolute terms and in relation to other means of transportation. Figure 1(a) shows how the number of international and domestic flights per person has developed between 1990 and 2015, when only traveling by Swedes is considered (connecting flights by internationals are, for example, excluded). As can be seen, there is a clear upward trend and the number of international flights per person per year has increased from around 0.5 to 1 during this time period. Looking at this graph, it is also important to keep in mind that far from everyone flies abroad in a given year, so the development among those who fly is even greater. Domestic flights per person is also included in the graph as a reference, and it is clear that this type of air travel follows a completely different pattern as it has been very stable over the same time period and even reduced a bit. As international air travel and hotel stays abroad are strong complements, it is not surprising that that the share of total expenditure that is spent on international travel (which includes both air travel expenditure and hotel expenditure) also has increased over the time period studied, as can be seen in Figure 1(b). Figure 1(c) shows how international travel by air has developed in relation to travel by train and boat by plotting the share of total number of trips from Sweden to another country that is made by air, including all types of travel and not just leisure travel. As can be seen, the share of international trips that is made by air is also increasing during the time period.

Figure 2 presents a graph of total expenditure, the measure of income that is used in this article (as discussed further in the Econometric Strategy section), as well as a graph of the price index for charter air travel. As is expected, income has been steadily increasing except for a few declines connected to the Swedish financial crisis of the early 1990s, the burst of the dot-com bubble in 2000
and the Great Recession in 2008. The development of the price index for charter air travel does however not show any clear trends.

Data

The data that are used in this article is the Household Budget Survey (HBS) for the years 2003–2009, and 2012 (the years 2010 and 2011 are not included as the survey was not conducted these years). The HBS is made by Statistics Sweden and includes detailed yearly expenditure data on the household level for all consumption categories in the COICOP classification system as well as general background information of both the household and its individuals. The yearly sample size is between 1972 and 2871 households and the total sample size for all years is 17,924 households. Each year a new sample of households is randomly selected, hence the full data set is repeated cross-section data and not panel data. The households are interviewed continuously throughout the year, and for infrequent purchases, such as leisure travel, the households report their purchases during the previous 12 months. Households who are interviewed at the beginning of a year will therefore mainly be answering for the previous year. Only households with a member younger than 79 are included in the survey. The main expenditure category of interest in this article is expenditure on international leisure travel. This expenditure category includes all types expenditures on leisure travel outside of Sweden and three variables are available: the total household expenditure on international leisure travel and two sub-categories that captures the expenditure that is made in Sweden (to a booking agency, airline or hotel, for example) and those expenditures that are made

Figure 1. Development of international travel: (a) International and domestic flights per person in Sweden, when only Swedish travelers are considered (b) Swedish international leisure travel expenditure share of total expenditure. (c) Share of total number of trips from Sweden to another country that is made by air, when all travel from Sweden by air, boat and train are considered. Flights data in (a) from Kamb and Larsson (2018), expenditure shares in (b) are the author’s own calculation from the Swedish Household Budget Survey for the years 2003–2012, micro-data from Statistics Sweden, and the shares in (c) are the author’s own calculations based on data from the following databases at Eurostat: “International transport of passengers from the reporting country to the country of disembarkation,” “Passengers embarked and disembarked in all ports by direction - annual data,” “International intra-EU air passenger transport by reporting country and EU partner country,” and “International extra-EU air passenger transport by reporting country and partner world regions and countries.”
once at the destination (such as food, local transportation but also hotels if the payment is made on arrival or during the trip), respectively. The dependent variable of choice in this article is total expenditure on leisure travel, but the other two available categories, expenditure and leisure travel made in Sweden and expenditure made on location, will however be used as dependent variables in a sensitivity analysis. Given the focus of this article, the main explanatory variable of interest is household income. To capture and correct for the fact that households smooth their consumption by saving and borrowing, in accordance with the permanent income hypothesis, total household expenditure is used as the main income variable in this article. If, for example, disposable income would be used as income variable instead the resulting estimates would likely be biased downward as the sensitivity in leisure air travel expenditure due to changes in disposable income, which is a measure of the current income, should be lower than the sensitivity to changes in permanent—or life—income. This is especially the case when a full representative sample of the population is used that includes households that use loans (such as students) or savings (such as retired individuals) for their consumption, which is the case for the sample that is used in this article. This choice is however not made completely without controversy as, for example, Alegre and Pou (2016) show that income elasticities estimated with disposable income (or current income), rather than the total expenditure, are significantly lower. Due to this, disposable income is used in a robustness check.

To control for potential endogeneity, a set of control variables is used. These are indicator variables to control for what type of city the household lives in (the three biggest cities in Sweden, medium sized cities, or if the household lives in a municipality smaller than 50,000 inhabitants, which is the baseline), what type of employment the main respondent in the household has (employed being the baseline), whether the main respondent in the household has a college education or not, and what year the household was interviewed in (i.e., yearly fixed effects variables). In addition, a variable that captures the size of the household and a variable for the age of the main respondent are also included as control variables. The control variables are all included to account for the possibility of omitted variable bias as it is likely that they are correlated with both the total expenditure of the household and the expenditure on international leisure travel. In addition to the

![Figure 2. Development of income and price of international air travel: (a) Total expenditure (b) Price index for package holidays. Total expenditure data from the database “Household consumption expenditure (ESA2010) by purpose COICOP. Year 1980–2017” from Statistics Sweden and price index data from the database “Harmonized Index of Consumer Prices (HICP), monthly data” from Eurostat.](image-url)
included control variables, other sources of endogeneity might be present. This is discussed further in the Possible endogeneity issues section.

To give a quick overview of some of the variables that have been described, descriptive statistics are presented in Table 1. There are a few aspects about the variables that are worth noting. International travel expenditure that is made in Sweden, such as air travel tickets and prebooked accommodation, is on average slightly larger than the expenditure that is made once the household has left Sweden. For the 75th (unconditional) expenditure quantile, the difference is larger, which is probably a result from larger prebooking fees for trips that are longer and further away. As expected, total expenditure exhibits a much lower dispersion compared to disposable income. As disposable income is income net from taxes a few households had negative disposable incomes, probably due to large infrequent tax payments in the year they were interviewed, at the same time as a few households had very large incomes (that possibly also is temporary). Total expenditure is much less dispersed, which is to be expected if households smooth their consumption. The age of household members and the household size both exhibit expected descriptive statistics.

Something that also becomes clear in Table 1 is that slightly more than half of the sample has zero expenditure on international leisure travel in the year of the sampling. This has implications for the econometric method used to estimate the income elasticities of interest, which is discussed in the next section.

**Econometric strategy**

To estimate the elasticities of interest, the following model is used

\[
\ln(T_i + 1) = \alpha + \beta(\tau)\ln I_i + \gamma(\tau)X_i + \epsilon_i
\]

where \(T_i\) = household \(i\)'s expenditure on international leisure travel, \(I_i\) = household \(i\)'s total expenditure, the chosen income variable, and \(X_i\) is a vector of control variables such as location dummies, household size, employment dummies, and yearly fixed effects, as described in more detail in the previous section. Worth noting is that control variables that concern personal, rather than household, attributes are only included for the reference person in the household as the inclusion of the same variables for other household members has little to no effect on the main coefficients of interest. The coefficients of interest are \(\beta(\tau)\), which can be interpreted as the income

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**Table 1. Descriptive statistics.**

| Variable               | Mean  | Std. dev. | Min. | Max.   | p.25  | p.50  | p.75  | N   |
|------------------------|-------|-----------|------|--------|-------|-------|-------|-----|
| Travel exp. total      | 13,783| 24,029    | 0    | 561,477| 0     | 0     | 20,766| 17,924|
| Travel exp. Swe.       | 7759  | 14,648    | 0    | 281,810| 0     | 0     | 10,760| 17,924|
| Travel exp. abroad     | 6021  | 12,799    | 0    | 334,570| 0     | 0     | 7524  | 17,924|
| Total exp.             | 355,083| 204,306  | 7731 | 3,168,246| 215,239| 317,573| 449,182| 17,924|
| Disp. income           | 427,251| 293,881  | 215,239| 317,573| 449,182| 17,924|
| Age 1st person         | 39.95 | 21.78     | 0    | 79     | 21    | 41    | 59    | 17,924|
| Age 2nd person         | 45.69 | 16.19     | 0    | 93     | 36    | 45    | 57    | 14,609|
| Age 3rd person         | 23.56 | 16.14     | 0    | 93     | 10    | 18    | 38    | 8804  |
| Age 4th person         | 12.91 | 11.75     | 0    | 90     | 5     | 11    | 16    | 5941  |
| Household size         | 2.79  | 1.37      | 1    | 11     | 2     | 2     | 4     | 17,924|
elasticity of the $\tau$th conditional quantile of the distribution of international leisure travel expenditure. The income elasticity will therefore be allowed to be different for different conditional quantiles of the expenditure on leisure air travel. Different income elasticities are in other words estimated for those households who, given their household characteristics, are, for example, low or high spenders of international leisure travel.

Since more than half of the sample has zero expenditures on international leisure travel, and since the log of zero is undefined, the dependent variable is transformed by adding a one to all observations. This is a common way to address the issue, but it also introduces the risk of bias, as shown by, for example, Bellemare and Wichman (2020). To avoid this risk, the inverse hyperbolic sine (IHS) transformation can be used instead. This transformation is also considered in this article, but as these estimates are very similar to the estimates when the $\ln(T_i + 1)$ transformation is used (see the sensitivity analysis in the Robustness checks section), the $\ln(T_i + 1)$ transformation is kept for the main analysis. The fact that less than half of the sample has a positive expenditure on leisure travel, while the rest of the sample has zero expenditure during the year of the sampling also means that the dependent variable is censored at zero. This introduces attenuation bias by construction if standard, ordinary least squared (OLS) based-based methods are used to estimate the elasticities of interest. Traditionally, different types of Tobit-based estimators have been used to address the issue of censoring. This includes the original Tobit estimator introduced by Tobin (1958) as well as different types of hurdle estimators (see, for example, Amemiya, 1984, for an overview). However, these estimators only produce consistent estimates if two rather strong parametric assumptions hold, namely, that the error terms are both homoscedastic and normally distributed, something that often is not the case. Two alternatives that can be estimated without these parametric assumptions are a basic two-part model, where probit or logit estimation is used for the participation decision and OLS regression for the quantity decision, and the sample selection model suggested by Heckman (1979), often denoted the Heckit model. However, both of these rely instead on assumptions of how the zeroes are generated, specifically if the zeroes are zeroes by choice (the two-part model) or due to some unobservable sample selection (the Heckit model). In addition to this, neither Tobit-based estimators nor the two-part or Heckit models allow for heterogeneous estimates of the coefficient of interest, which is needed to estimate the income elasticities of interest in equation (1). In part due to these limitations, censored quantile regression (CQR) is instead used as the main method of estimation in this article. Censored quantile regression is a semi-parametric method developed by Powell (1984, 1986) as an extension of the quantile regression framework introduced by Koenker and Basset (1978). Contrary to Tobit estimators, CQR is invariant to both the distribution of the error terms and to potential heteroscedasticity. The method also produces consistent estimates regardless of the reason for the zeroes to exist in the sample as no assumptions regarding the data generating process is needed. Hence, the exact reason for some of the households to choose a zero expenditure on international leisure travel does not need to be known in order to estimate the income elasticities for the different conditional quantiles for those households who have a positive expenditure on this good. In addition to this, censored quantile regression gives insight into how the whole conditional distribution of the dependent variable is affected by changes in the variables of interest as estimates at different conditional quantiles of the dependent variable can be estimated. CQR thus enables the estimation of the type of heterogeneous income elasticities that is of interest in this article. While CQR is the main method of estimation in this article, standard Tobit and two-part estimates are also included for comparison. Even though Tobit estimates are likely biased, as discussed above, it is still interesting to include this estimate since Tobit is still a popular method that many can relate to. In addition, two-part estimates are included to provide an estimate of the average income elasticity. The two-part model is chosen instead of the Heckit model since it is better suited when the zeroes in the dependent variable
are “true” zeroes, that is, when the zeroes are a result of the household decision and not due to sampling selection, which is likely the case for the consumption of international leisure travel. The two-part model is estimated using the “twopm” package, written by Belotti et al. (2015) and average marginal effects, the elasticity in the case of income, are calculated using the built in Stata package “margins.” In the following subsections, the CQR model, how it is estimated, how the estimated coefficients are to be interpreted and possible endogeneity issues are described and discussed in more detail.

Censored quantile regression

For a model linear in the coefficients, such as the general linear model

$$y_i = x_i' \beta + u_i$$  \hspace{1cm} (2)

the conditional regression quantile $Q_{y|x}(\tau)$ is given by

$$Q_{y|x}(\tau) = x' \beta(\tau)$$  \hspace{1cm} (3)

where the coefficients $\beta(\tau)$ are (or at least are allowed to be) different for each quantile. The $\tau$th sample quantile is found by solving the minimization problem

$$\min_{\beta} \sum_{i=1}^{n} \rho_{\tau}(y_i - x_i' \beta)$$  \hspace{1cm} (4)

where $\rho_{\tau}(\cdot)$ is a check-function such that $\rho_{\tau}(\lambda) = (\tau - 1(\lambda < 0)) \lambda$. Hence

$$\rho_{\tau}(y_i - x_i' \beta) = \begin{cases} y_i - x_i' \beta & \text{if } y_i > x_i' \beta \\ (\tau - 1) (y_i - x_i' \beta) & \text{if } y_i \leq x_i' \beta \end{cases}$$  \hspace{1cm} (5)

The estimation of the coefficients $\beta(\tau)$ is thus a minimization of asymmetrically weighted absolute residuals, which can be compared with classical regression methods that instead are based on a minimization of squared residuals.

In the case of left-censoring at $C$, $y$ is only observed if $y^* > C$ and $C$ is observed if $y^* \leq C$, and the conditional regression quantile is now instead given by

$$Q_{y|x}(\tau) = \max \left[ C, x_i' \beta(\tau) \right]$$  \hspace{1cm} (6)

The standard estimator for this censored quantile regression model is the Powell (1986) estimator

$$\min_{\beta} \sum_{i=1}^{n} \rho_{\tau}(y_i - \max[C, x_i' \beta])$$  \hspace{1cm} (7)

where $\rho_{\tau}(\cdot)$ is the same check-function as before. Given that the estimation of this estimator is successful, it provides consistent $\beta(\tau)$ estimates, as shown by Powell (1986). In practice however, estimation of this partially linear minimization problem, which needs to be estimated using numerical methods, often has issues with convergence. Several attempts to facilitate the estimation have been made, see, for example, Buchinsky (1994), Buchinsky and Hahn (1998) and Khan and Powell (2001), and the method that will be used in this article is the three-step procedure developed by Chernozhukov and Hong (2002), described below.
The three-step censored quantile regression estimator

The first step in this method is to estimate a probability model where the probability of a non-censored observation is predicted

\[ \delta_i = p(X_i'\beta) + \epsilon_i \] (8)

where \( \delta_i \) takes the value 1 if the observation \( i \) is not censored and 0 otherwise, \( p(\cdot) \) is a probability function modeled by probit in this article, and \( X' \) indicates the desired transforms of \((X_i, C_i)\). Using this estimation, the sub-sample \( J_0 = \{i : p(X_i'\beta) > 1 - \tau + c\} \) is constructed, where \( c \) is a trimming constant strictly between 0 and \( \tau \) used to reduce the risk of projecting observations that are not truly non-censored due to a misspecified probability model. The second step is to run a standard quantile regression estimation on the projected sub-set \( J_0 \) from the previous step. Hence, \( \beta_0(\tau) \) is estimated through the minimization problem given in equation (4) using the sub-set \( J_0 \). This initial estimator is consistent but inefficient. To increase the efficiency, a new sub-set \( J_1 \) is constructed using the estimated \( \beta_0(\tau) \) coefficients such that \( J_1 = \{i : X_i'\hat{\beta}_0(\tau) > C_i + v_n\} \) where \( v_n \) is a small positive number such that \( \sqrt{n} \times v_n \rightarrow \infty \) and \( v_n \rightarrow 0 \). The third step is to once again run a standard quantile regression estimation but using the new sub-set \( J_1 \), resulting in an estimator that is both consistent and efficient. To estimate this, the CQIV Stata module written by Chernozhukov et al. (2012) is used with the exogenous option that allows for estimation of the three-step CQR estimator. The trimming constant \( c \) in the first step described above is allowed to be the default, which is 0.03. Hence three percent of the sample is trimmed to reduce the risk of a misspecified probability model. Standard errors for the estimated coefficients are obtained through a non-parametric bootstrap procedure where the number of repetitions is also the default in the CQIV module, which is one hundred, and the used seed number is 1477. A higher repetition has also been considered, which only results marginally smaller standard errors but do not affect the results.

Interpretation of estimated coefficients

The interpretation of the estimated coefficients is the same as for standard quantile regression estimates. The estimated coefficients are the partial derivatives of the conditional quantile of \( y \) with respect to the regressor of interest. For regressor \( j \), this is given by \( \frac{\partial Q_{y|X_j}(\tau)}{\partial x_{ij}} = \beta_j(\tau) \). As described by, for example, Buchinsky (1998), this derivative is to be interpreted as the marginal change in the \( \tau \)th conditional quantile due to the marginal change in the \( j \)th regressor. As both the expenditure on international leisure travel and total expenditure are log-transformed, \( \beta(\tau) \) in equation (1) can be interpreted as the income elasticity for the \( \tau \)th conditional quantile of the expenditure on international leisure travel directly. That is, how much (in percent) the expenditure of international leisure travel increases when total expenditure increases by one percent, for the conditional quantile of interest. As the CQR estimator is a conditional estimator, it is important to keep in mind that the estimated coefficients should be interpreted with respect to the covariates that are included in the model. Hence, the interpretation is slightly different from OLS-based methods where the law of iterated expectations allows estimates for the conditional expected value to also be interpreted for the unconditional expected value. The income elasticity for a high conditional quantile should therefore be interpreted as the income elasticity for those households who have a high expenditure on international leisure travel given their observable household characteristics that have been controlled for. Another, perhaps more intuitive, way to interpret the estimates is provided by Kowalski (2016) who explains the conditional quantile treatment effect by comparing two
groups of people with the same observable characteristics but who differ in the main variable of interest, income in our case. The estimated income elasticity in this article is then the percentage difference in expenditure on international leisure travel between two groups that have the same covariates but where one of the groups has one percent higher total expenditure than the other group.

Possible endogeneity issues

While the censored quantile regression framework successfully deals with the bias that comes from the censoring mechanism, potential issues with endogeneity still remain. One such concern is the possible issue of self-selection, especially that those who wish to travel internationally self-select into higher total expenditure brackets because of this wish. For this to be an issue however, increased expenditure on international leisure travel must be specifically targeted by the households. If the households self-select into higher income brackets just to consume more in general, no such issue exists. While there might be a few occurrences of these travel fanatics, we argue that most households strive for higher income brackets to increase their overall consumption and that if this bias is present, it is limited. Another concern is that there might be omitted variables that affect both total expenditure and the expenditure on leisure travel. Apart from the variables that are already controlled for, it is however not clear what omitted variables could be an issue. While it is important to show some caution when interpreting the estimated income elasticities, we argue that issues with endogeneity, if present, should be small as there are no obvious issues that are not addressed.

Main results

The main estimates of interest are the estimated income elasticities, the coefficients before \( \ln I \) in equation (1), for different conditional quantiles. For the main analysis, this is estimated for all the years included in the data set (i.e., 2003–2009 and 2012). For the analysis of the distributional effect of the financial crisis in 2008, two separate estimations are made: one for the year 2007 and another for the year 2009. The estimated quantile effects are then compared.

In Table 2, the estimates for the main analysis are presented for every 10th quantile between 55 and 95 when the three-step CQR estimation method is used (due to the censoring, the first quantile with positive expenditure is the 51st quantile). Tobit and two-part model estimates are also included for comparison. For brevity, only the income elasticity coefficient estimates are included in Table 2, but in all estimations, the full set of covariates has been included. Full estimation tables where all the covariates are included are provided in the Online Appendix A1. The income elasticity estimates are also plotted in Figure 3, for quantiles larger than 50, where the two-part estimate is included as a straight line for comparison.

As can be seen in both Table 2 and Figure 3, the CQR estimations show overall high income elasticities that start very high for the lower conditional quantiles, those households who spend the least on international leisure travel compared to their compeers, and decrease steadily as spending on international leisure travel increases. As the estimates can be interpreted as income elasticities directly, it can be seen that for the 55th conditional quantile the estimated income elasticity is about 5. This means that when income increases by 1%, expenditure on leisure travel increases by approximately 5% for households that spend relatively little on international leisure travel. For those households who spend the most on international leisure travel compared to households with similar background characteristics, the income elasticity estimates are around 1. For those households who spend the least on international leisure travel compared to their compeers therefore, international leisure travel is a strong luxury good. As households spend more money on international leisure travel, the income elasticity steadily reduces until it reaches levels that are close to unit elasticity for
the highest spenders, conditional on the covariates. The average income elasticity, as estimated with the two-part model, is very close to 3, which is slightly higher than the average estimated in the meta-analysis made by Peng et al. (2015). Worth noting is that the elasticity estimated using Tobit is way off in relation to both the CQR and two-part estimation, indicating that caution should be shown when using this method in cases where heterogeneous effects are to be expected.

These results have several practical implications for both policy makers and managers in the tourism industry. For managers in the tourism industry, the observed heterogeneity in income elasticities can be used to improve the efficiency of marketing efforts. Since travel agencies, hotels, and airlines often have customer data on how much households spend on their tourist products (as well as other background characteristics), they can target households who consume relatively little on their product with offers that simulate increased income. One example could be extra bonuses or “miles” for the first dollars that are spent on their product. Also, they can coordinate marketing toward low-expenditure households with policy measures that boost income levels, such as stimulus

| Variables | Quantile 55 | Quantile 65 | Quantile 75 | Quantile 85 | Quantile 95 |
|-----------|-------------|-------------|-------------|-------------|-------------|
| ln I, CQR | 5.331***    | 2.170***    | 1.466***    | 1.124***    | 0.952***    |
|           | (0.123)     | (0.0488)    | (0.0335)    | (0.0260)    | (0.0257)    |
| ln I, Tobit | 5.710***     |             |             |             |             |
|           | (0.147)     |             |             |             |             |
| ln I, two-part | 2.974***   |             |             |             |             |
|           | (0.0720)    |             |             |             |             |

Standard errors in parentheses. Tobit and two-part estimates are average marginal effects and not estimated for each quantile. ***p < 0.01, **p < 0.05, *p < 0.1.

Adjusted $R^2$ two-part model: 0.0914 (1st step) and 0.1646 (2nd step).
Prob > F two-part model: 0.0000 (in both 1st and 2nd steps).

Figure 3. Estimated income elasticities with corresponding confidence intervals. CQR estimates for the quantiles 51 to 99. Two-part estimate included for comparison.
checks or tax-cuts, as these households are more likely to spend more money on tourism products. From policy makers point of view, fiscal policy to boost the economy through increased disposable income will be very effective to increase the demand for tourism products, and this increased demand will mainly be driven by the households who spend the least on the product. In addition, policy that affects the price of tourism (aviation taxes, for example) is likely to affect the low spenders more than high spenders (since price effects are driven by both substitution and income effects).

The theoretical results in Matsuyama (2002) and Morley (1998) can also be used to understand the distribution of income elasticities that is estimated. The observed pattern is exactly what is expected by Matsuyama’s (2002) theory for a luxury product that has reached some market maturity as international tourism is a strong luxury good for those who spend the least on it and then continuously goes toward being a necessity for households who spend the most on the good. The U-shape pattern that is hypothesized by Morley (1998) on a country level also seems to be present on a household level, when expenditure levels rather than income are considered, at least for the part of the curve that can be estimated. As the household equivalent of the relatively poor countries will not afford to travel internationally, their income elasticity cannot be estimated. The curve instead starts at the equivalent of middle income countries, those who can just afford to travel internationally so that half of Morley’s U-shape pattern is visible. One theoretical implication of this result is thereby that the estimated pattern of income elasticities can be seen as a snap-shot of the market penetration of outbound international tourism in Sweden. As income levels, and thereby tourism expenditure levels, continue to increase, the market will mature further as more households start to see international tourism as a necessity rather than a luxury, and this “flattening” of the curve will have a downward pressure on the average income elasticity. This also suggests that the annual growth rate of international tourism will, at least at some point, decrease as the international tourism market matures. This does however also depend on whether the shape of the income elasticity curve along the expenditure distribution is the same in other countries. Understanding this type of household heterogeneity can therefore also be useful in forecasting models. Applying the intuition from Morley (1998) on the results also suggests that a larger share of households might participate in international tourism as income levels continue to increase. This is however not necessarily the case, as income constraints is far from the only reasons that households choose not to travel internationally.

Another theoretical prediction in Matsuyama (2002) is also that the price of the good will decrease due to economies of scale as the demand of it increases. This is applicable to some aspects of international tourism, but not as much in others. The long term trend of decreasing prices in the air travel sector could, for example, in part be explained by this type of reasoning: as demand increases, and the good is not seen as the highest of luxury any more, the airlines can use advantages of economies of scale and expand the market by introducing low price carriers. Other parts of international tourism are however more labor intensive, and this type of downward pressure due to economies of scale in the production process will not be present to the same degree. It is therefore far from given that one should expect decreasing price levels in international tourism as a whole, and as we saw in Figure 2(b) in the Literature Review and Empirical Background section the price index for international travel from Sweden has been trendless between 1980 and 2017. Matsuyama’s theory together with the presented results also has implications for how the aggregate “good” of international tourism develops over time. As households get richer over time, what is part of their international travel portfolio changes and includes more of the items that previously only the richest households could afford. One clear example is in the choice of transportation. Not long ago, very few households could afford to travel by air and went abroad by train, boat (in the countries where it
was possible), or by car. As households became richer, more and more turned to air travel, which in Sweden has resulted in that more than 90% of all international travel currently is made by air. Similar developments can be seen in the choice of destination, which in part is connected to the choice of transportation. Bali was once a destination of a life time for most Swedes, if even that, now it has become a common destination for middle class households. As air travel slowly is going toward becoming a necessity for most tourists, by Matsuyama’s theory, it is only a matter of time until the “next” luxury good appears. One can of course only speculate what good this could be, but space tourism could, for example, be one interesting candidate, something that is suggested by, for example, Hart (2018). Regardless of what exactly the “next luxury” will be, the international tourism product is dynamic and constantly changing. Those actors in the industry who can predict what the next luxury will be, or perhaps even influence it themselves through marketing, will also likely get a competitive advantage in the industry. The predicted decrease in the income elasticity for international tourism at the aggregate level will also likely be slowed down if the level of luxury in the good is updated continuously.

Turning next to the distributional effect of the financial crisis, the estimated income elasticities for each conditional quantile in the year before and after the crisis year is presented in Figure 4. As can be seen, there seems to be a small distributional shift outward with the post-crisis income elasticities being slightly larger than the pre-crisis elasticities, for almost all quantiles. The standard errors are however much larger for these two estimations, which of course is expected since the sample size for each estimation is considerably smaller than in the full estimation, and while the income elasticities are still significant the confidence intervals for the 2 years are overlapping for many quantiles. Hence, a null hypothesis that the income elasticities are the same before and after the crisis cannot be rejected for many quantiles. Even though a clear tendency can be seen when looking at the point estimates for the 2 years, it cannot be definitely concluded that the income elasticities are larger after the 2008 financial crisis, at least for the whole distribution. These results go in line with the results in Alegre and Pou (2016). This means that the Swedish households’ sensitivity to income changes remains robust after the financial crisis of 2008, which is good news as this means that the demand for international tourism should recover fast as income levels starts to

![Figure 4. Estimated income elasticities with corresponding confidence intervals for the year before and after the 2008 financial crisis. CQR estimates for the quantiles 51 to 99.](image-url)
increase again (which is also what happened, as can be seen in Figure 1 in the Data section). In particular, this robustness is more or less the same along the whole expenditure distribution. When applying these results on the current COVID-19 pandemic and the resulting global economic downturn two things can be said. As traveling restrictions become looser, there will still exist a downward pressure on international tourism due to decreases in income levels as a result of the economic downturn around the world. However, when income levels start to increase again the demand is likely to increase fast due to the high income elasticities. Of course, this does not take into account any behavioral effects that the COVID-19 crisis has had on international travelers, which may very well be present in both directions (that people travel internationally more than before to “catch up” missed travel opportunities or that they travel less as the concern for contamination is still present).

Robustness checks

We now turn to robustness checks. First, the covariates that are used are introduced in a step-wise fashion to examine how sensitive the estimates are to new control variables. As can be seen in Table 3, which presents the results for the 55th conditional quantile estimated with CQR, the estimated coefficient for $\ln I$ is stable during this procedure. This gives an implicit indication that omitted variable bias might not be a big issue in the estimation. The estimation for the 55th conditional quantile is also the estimation that is the least stable to the step-wise inclusion of the covariates of all the estimated quantiles. Similar step-wise inclusions for estimations at the other estimated quantiles are even more stable to this procedure.

Second, it could be that the estimates are sensitive to the precise definition of the dependent or main explanatory variable. In the case of the dependent variable, the one that is used in the main specification is the total expenditure on international leisure travel that the household has in a year. Since data on expenditures made in Sweden only, such as expenditure on air travel and pre-paid hotels, as well as data on expenditures made on location are available separately, it is possible to examine how sensitive the estimates are to alternative definitions of the main dependent variable. The main specification is therefore here estimated using the variable that captures the expenditure on international leisure travel that is only paid in Sweden (such as expenditure on air travel and pre-paid hotels), as well as the part that is paid once on location, as the dependent variable separately. As can be seen in Table 4, the estimates when these two variables are used as the dependent variable are however very similar to the corresponding estimations in Table 2. The estimates do therefore not seem to be sensitive to the exact definition of the dependent variable. Similarly, in the case of the main explanatory variable, one could argue that using total expenditure as the income variable instead of disposable income might yield biased estimates. As can be seen in Table 4 however, this is likely not the case as the estimates when the log of disposable income is used as the main explanatory variable instead of the log of total expenditure (keeping the dependent variable the same as in the main specification) are also similar to the estimates when total expenditure is used. The only difference is that the estimates are slightly lower, which is to be expected since consumption of leisure travel most likely is smoothed through savings or credit, something that is not accounted for when disposable income is used as the income variable.

As there could be a potential bias from the fact that a 1 is added to the dependent variable before it is logged, the inverse hyperbolic sine transformation is also considered. According to Bellemare and Wichman (2020), this transformation takes care of the potential source of bias at the same time as the resulting estimates can be interpreted in the same way as when the log-transformation is used, as long as the mean of the variable is large enough (larger than 10 is a suggested limit, which is the case
in this paper). As can be seen in Table 5, the estimates of the income elasticity for most estimations are very similar to the estimates when the log-transformation is used.

In addition to the ones that have been examined here, a sensitivity analysis has also been done with regard to different censoring points, where slightly higher censoring points are used instead of 0.

### Table 3. Step-wise inclusion of covariates for the 55th quantile using CQR estimation.

| Variables                          | (1)         | (2)         | (3)         | (4)         | (5)         | (6)         |
|------------------------------------|-------------|-------------|-------------|-------------|-------------|-------------|
| ln I                               | 5.760***    | 6.728***    | 5.913***    | 5.393***    | 5.319***    | 5.331***    |
|                                    | (0.141)     | (0.169)     | (0.131)     | (0.138)     | (0.129)     | (0.123)     |
| Family size                        | –1.002***   | –0.918***   | –0.882***   | –0.820***   | –0.808***   | –0.808***   |
|                                    | (0.0650)    | (0.0504)    | (0.0545)    | (0.0556)    | (0.0535)    |             |
| Big city                           | 3.280***    | 2.556***    | 2.559***    | 2.607***    |             |             |
|                                    | (0.145)     | (0.150)     | (0.140)     |             |             |             |
| Medium city                        | 1.927***    | 1.444***    | 1.430***    | 1.429***    |             |             |
|                                    | (0.145)     | (0.150)     | (0.140)     |             |             |             |
| Entrepreneur, 1st member           | 0.211       | 0.0838      | 0.0881      |             |             |             |
|                                    | (0.296)     | (0.282)     | (0.269)     |             |             |             |
| Student, 1st member                | 1.166***    | 1.310***    | 1.406***    |             |             |             |
|                                    | (0.220)     | (0.210)     | (0.201)     |             |             |             |
| Unemployed, 1st member             | –2.303***   | –2.545***   | –2.303***   |             |             |             |
|                                    | (0.432)     | (0.388)     | (0.372)     |             |             |             |
| Retired/stay-at-home, 1st member   | –1.469***   | –1.779***   | –1.636***   |             |             |             |
|                                    | (0.180)     | (0.201)     | (0.192)     |             |             |             |
| Other employment, 1st member       | –1.804***   | –1.698***   | –1.844***   |             |             |             |
|                                    | (0.561)     | (0.529)     | (0.523)     |             |             |             |
| Educated, 1st member               | 1.483***    | 1.381***    | 1.369***    |             |             |             |
|                                    | (0.150)     | (0.143)     | (0.137)     |             |             |             |
| Age first person                   | 0.0115***   |             |             | 0.0123***   |             |             |
|                                    | (0.00390)   |             |             | (0.00373)   |             |             |
| Year 2004                          |             |             |             | 0.528**     |             |             |
|                                    |             |             |             | (0.225)     |             |             |
| Year 2005                          |             |             |             | 0.623***    |             |             |
|                                    |             |             |             | (0.231)     |             |             |
| Year 2006                          |             |             |             | 0.489**     |             |             |
|                                    |             |             |             | (0.237)     |             |             |
| Year 2007                          |             |             |             | 0.868***    |             |             |
|                                    |             |             |             | (0.224)     |             |             |
| Year 2008                          |             |             |             | 0.768***    |             |             |
|                                    |             |             |             | (0.228)     |             |             |
| Year 2009                          |             |             |             | 0.616***    |             |             |
|                                    |             |             |             | (0.230)     |             |             |
| Year 2012                          |             |             |             | 0.942***    |             |             |
|                                    |             |             |             | (0.215)     |             |             |
| Constant                           | –66.82***   | –76.43***   | –68.19***   | –61.41***   | –61.04***   | –61.93***   |
|                                    | (1.789)     | (2.067)     | (1.595)     | (1.690)     | (1.584)     | (1.514)     |
| Observations                       | 17,379      | 17,377      | 17,378      | 17,380      | 17,378      | 17,379      |
The results from this sensitivity check are included in Online Appendix A2, where the estimation is done for the 55th quantile, and show little to no effect on the estimated income elasticities. Overall the estimated income elasticities are therefore robust to the possible sources of bias that can be checked for.

## Conclusion

In this paper, we estimate heterogeneous income elasticities of international leisure travel demand for Swedish households based on their relative consumption levels. This is done using the Swedish Household Budget survey for the years 2003–2009 and 2012 where estimation is made with censored quantile regression. The results show that a great heterogeneity in the income elasticities exists, being the highest for the households who consume the least of international tourism relative to their peers, with an estimated income elasticity of 5.3, and then steadily decreasing as the relative expenditure on the good increases until it reaches an income elasticity of less than 1 for the relative top spenders of the good. The results further show that the effect of the financial crisis on the distribution of income elasticities is minimal, although a small tendency for an outward shift in the distribution is present, with overall larger income elasticity estimates the year after the crisis than the year before.

### Table 4. Income elasticity estimates for alternative travel expenditure and income variables.

| Dependent variable | Quantile 55 | Quantile 65 | Quantile 75 | Quantile 85 | Quantile 95 |
|--------------------|-------------|-------------|-------------|-------------|-------------|
| ln (T_{abroad} + 1), CQR | 4.861*** | 2.857*** | 1.615*** | 1.261*** | 0.993*** |
|                     | (0.100) | (0.0665) | (0.0325) | (0.0339) | (0.0320) |
| ln (T_{Sweden} + 1), CQR | 5.044*** | 2.961*** | 1.681*** | 1.193*** | 0.999*** |
|                     | (0.133) | (0.0797) | (0.0369) | (0.0272) | (0.0263) |
| ln (l_{asp}), CQR | 4.668*** | 1.878*** | 1.229*** | 0.798*** | 0.674*** |
|                     | (0.121) | (0.0482) | (0.0357) | (0.0252) | (0.0287) |

Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

### Table 5. Income elasticity estimates when the IHS transformation is used.

| Variables          | Quantile 55 | Quantile 65 | Quantile 75 | Quantile 85 | Quantile 95 |
|--------------------|-------------|-------------|-------------|-------------|-------------|
| IHS (l), CQR       | 5.682*** | 2.170*** | 1.467*** | 1.124*** | 0.952*** |
|                     | (0.130) | (0.0489) | (0.0341) | (0.0260) | (0.0257) |
| IHS (l), Tobit     | 6.083*** | 2.170*** | 1.467*** | 1.124*** | 0.952*** |
|                     | (0.157) | (0.0489) | (0.0341) | (0.0260) | (0.0257) |
| IHS (l), two-part  | 3.160*** | 2.170*** | 1.467*** | 1.124*** | 0.952*** |
|                     | (0.0771) | (0.0489) | (0.0341) | (0.0260) | (0.0257) |

Standard errors in parentheses. IHS: inverse hyperbolic sine. Tobit and two-part estimates are average marginal effects and not estimated for each quantile. *** p < 0.01, ** p < 0.05, * p < 0.1 adjusted $R^2$ two-part model: 0.0914 (1st step) and 0.1645 (2nd step). Prob > F two-part model: 0.0000 (in both 1st and 2nd steps).

The results from this sensitivity check are included in Online Appendix A2, where the estimation is done for the 55th quantile, and show little to no effect on the estimated income elasticities. Overall the estimated income elasticities are therefore robust to the possible sources of bias that can be checked for.
The results can be used by managers in the tourism industry and governmental policy makers alike. For the tourism industry, the largest effect on sales can be achieved if households with relatively low travel consumption are targeted in marketing efforts. Marketing that simulates income increases, such as end of year bonuses, will likely be very effective when addressed specifically to these households. Marketing can also be coordinated with stimulus checks or other governmental policy measures that increases households’ income. From a governmental policy point of view, it is clear that policy that affects income will also have a large effect on the demand for international tourism, and that this is especially driven by the low spenders. As the distribution of income elasticities remained stable when the 2008 financial crisis hit, it is likely that the economic parts of the decreased tourism demand will recover as the world starts to open up after the COVID-19 pandemic, at least in Sweden. Of course, there are also a lot of other behavioral aspects that can affect the recovery of international tourism that have not been addressed in this paper.

The results together with the theoretical predictions of Matsuyama (2002) and Morley (1998) also increase the understanding of structural change in demand for international tourism, and why global income elasticities seem to decrease over time (as found by, for example, Gunter and Smeral, 2016). The estimated pattern of elasticities becomes a snap-shot of this process, and as more and more households start to view the good as a necessity the average income elasticity decreases, as well as the growth rate of international tourism demand. In addition, the results also provide some theoretical implications for price changes in the tourism industry as well as how the international tourism “good” develops in terms of luxury, specifically when it comes to the mode of transportation and type of destination.

Further research is however needed. Even though this paper is an important contribution, the literature on this type of heterogeneity is still very sparse. Similar analyses should be done for other countries as different countries likely are in different stages of the market maturity. One limitation with this article is also that the data are 10 years old, and research with newer data would therefore be very helpful. Further analysis with regard to the COVID-19 pandemic is also warranted as the current crisis at its heart is not an economic crisis. It is also possible that accounting for this type of heterogeneity can help improve forecasting accuracy, much like Smeral (2017) showed at an aggregate level, which also is an interesting area of future research.

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Supplemental material

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