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Income Inequality and Happiness: A Meta-Analysis

Master's thesis

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Declaration of Authorship

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Abstract

The relationship between income inequality and happiness is central to a host of welfare policies. If higher income inequality puts people down, advocating for income redistribution from the rich to the poor could make society happier. We show, however, that this popular consensus on the relationship's direction is rather absent in the academic literature. Based on the 868 observations collected from 53 studies and controlling for 62 aspects of study design, we use state-of-the-art meta-analysis techniques to identify several important drivers of the effect. Unless each study gets the same weight, the literature is driven by publication bias pushing the estimates against the popular consensus. While geographical differences dominate among the systematic influences of the relationship's magnitude, the relationship is also strongly affected by various methods and data the authors use in the primary studies. Most prominently, it matters if authors control for different individual's characteristics, such as perceived trust in people or their health status.

JEL Classification	C83, C11, D31, I31, C82
Keywords	meta-analysis, income inequality, well-being, happiness, bayesian model averaging, publication bias
Title	Income Inequality and Happiness: A Meta-Analysis

Abstrakt

Vztah mezi ekonomickou nerovností a štěstím je ústředním bodem řady sociálních politik. Pokud vysoká ekonomická nerovnost škodí lidem, pak podpora přerozdělování příjmů od bohatých k chudým může učinit společnost šťastnější. Ukazujeme však, že v akademické literatuře tento populární konsenzus ohledně směru vztahu spíše chybí. Na základě 868 pozorování shromážděných z 53 studií, kontrolováním 62 aspektů designu studie a používáním nejmodernějších meta-analytických technik, identifikujeme několik důležitých faktorů efektu ekonomické nerovnosti na štěstí. Pokud nemají všechny studie stejnou váhu, je v literatuře přítomna publikační selektivita upřednostňující odhady proti populárnímu konsensu. Zatímco geografické rozdíly dominují mezi systematickými vlivy velikosti vztahu, vztah je také silně ovlivněn různými daty a metodami, které autoři v primárních studiích používají. Dále záleží, jestli při odhadování efektu autoři kontrolují různé individuální charakteristiky, jako například důvěru lidí ve společnost nebo jejich zdraví.

Klasifikace JEL	C83, C11, D31, I31, C82
Klíčová slova	meta-analýza, ekonomická nerovnost, štěstí, bayesian model averaging, publikační selektivita
Název práce	Ekonomická nerovnost a percepce štěstí: Meta-analýza

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Contents

List of Tables

List of Figures

Acronyms

BMA Bayesian Model Averaging

CGSS Chinese General Social Survey

DS Deininger and Squire

ESS European Social Survey

EVS European Values Survey

FAT Funnel Asymmetry Test

FE Fixed Effects

FMA Frequentist Model Averaging

GDP Gross Domestic Product

IV Instrumental Variable

MRA Meta-Regression Analysis

OECD Organisation for Economic Co-operation and Development

OLS Ordinary Least Squares

PCC Partial Correlation Coefficient

PET Precision Effect Test

PIP Posterior Inclusion Probability

PM Posterior Mean

PMP Posterior Model Probabilities

PSD Posterior Standard Deviation

RE Random Effects

SD Standard Deviation

SE Standard Error

SWB Subjective Well-Being

SWIID Standardized World Income Inequality Database

UIP Unit Information Prior

WAAP Weighted Average of the Adequately Powered

WB World Bank

WIID World Institute for Development Economics Research

WLS Weighted Least Squares

WVS World Values Survey

Master's Thesis Proposal

Author	Bc. Lucie Kamenicka
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Proposed topic	Inequality and Happiness: A Meta-Analysis

Motivation More than 70 years ago Duesenberry (1949) argued that people do not care as much about being poor as they care about feeling poor: relative not absolute wealth matters. Number of more recent studies (Alesina et al., 2003; Benabou & Ok, 2001; Dynan & Ravina, 2007, or Oishi et al., 2011, to name but a few) show that income inequality is rather badly perceived in different contexts. It follows that any government that wants to make people happier pushes towards policies favouring social transfers, redistributing income from the rich to the poor. Aggregate datasets support part of such story: the share of social transfers on economic output continues to increase (OECD, 2020) and people are getting richer (WB, 2020). But also, continuously larger share of people report life satisfaction and happiness equality (WVS, 2016, Clark et al., 2016) while the trend in income inequality, whether increasing or not, seems to be strongly dependent on a chosen reporting metrics (compare Piketty & Saez, 2014, to Auten & Splinter, 2019, for example).

These crude trends in data suggest that the role of income inequality in predicting subjective well-being is controversial, to say at least. The empirical research agrees: some authors find the relationship to be negative (Oishi et al., 2011; Wilkinson & Pickett, 2009), some find it to be positive (Rozer & Kraaykamp, 2013; Berg & Veenhoven, 2010), and some do not find any (Graham & Felton, 2006; Zagorski et al., 2014). The two qualitative literature reviews written on the topic (Ferrer-i-Carbonell & Ramos, 2013, and Schneider, 2016) and the meta-analysis of Ngamaba et al. (2017) testify to a large heterogeneity present in these studies: there could be certain aspects of data and measurement choice systematically driving the resulting reported relationship between income inequality and happiness. The regional differences (Alesina et al., 2003), income mobility (Oishi et al., 2011), economic development (Berg and Veenhoven, 2010), and political orientation (Alesina et al., 2003) are just a few examples of the assumed correlates.

I find, however, several features of the meta-analysis by Ngamaba et al. (2017) worrisome and the goal of my thesis will be to carefully address these features. First, the authors work with 24 studies only (24 observations) which sheds doubt on the statistical power of their results. I plan to enlarge the dataset, especially along the lines of economics research (but will include psychology studies as well). Second, the authors do not account for publication bias, the tendency of people involved in the publication process to preferentially publish estimates that make for a good story. I hypothesize that publication bias could play a substantial role in pushing the reported estimates upward. Third, Ngamaba et al. (2017) test only for pairwise differences between certain aspects of study design, they do not perform a multivariate analysis. I plan to use the state-of-the-art meta-analysis tools to address the heterogeneity (and publication bias) in the literature. I also plan to add more aspects of study design that can systematically affect the results: data aggregation, data dimension, methods used, or quality of the study. Fourth, I find the analysis scarce on economic interpretations and would like to contribute with a more thorough discussion of the heterogeneity behind the estimates. Fifth, I will attempt to construct a synthetic study which would consider best-practice study design and I will estimate the best-practice effect.

Hypotheses

Hypothesis #1: Publication bias is present in the literature estimating the relationship between inequality and happiness.

Hypothesis #2: Publication bias exaggerates the mean value of the relationship between inequality and happiness reported in the empirical literature.

Hypothesis #3: The estimated effects on the relationship between inequality and happiness are driven by the level of country's development.

Methodology First, I need to create a dataset from primary studies. I will start by constructing a search query for Google Scholar that is superior to all other databases because it uses a powerful full-text search and does not discriminate as to the research field. Second, I will make sure the studies already reviewed by others, including Ferrer-i-Carbonell & Ramos (2013), Schneider (2016), and Ngamaba et al. (2017), are included in my list. Moreover, since the sample used by Ngamaba (2017) ends in October 2017, I will focus my search on novel studies published since then. There are several challenges I will presumably face: first, the reported effects might come in form of a regression coefficient or correlation coefficient and I will have to standardize the effects in order to make them comparable. Second, I will need to collect some measure of precision of the effect that will allow me to test and treat for potential publication bias (standard error, number of observations, standard deviation, confidence intervals, etc). I might also collect the effects that do not have any measure of precision reported but those effects will not be used in the quantitative treatment of publication bias. If I find the publication bias not to be present in the literature, the effects absent measure of precision could be used for the analysis of heterogeneity, as well.

To test for the presence of publication bias, I will perform a commonly used visual test called the funnel plot (Egger et al., 1997). I will, however, also perform several more rigorous alternatives, including the linear test called Funnel Asymmetry Test (Stanley, 2005) with different variants of data weighting, and some newly developed non-linear tests, including the Weighted average of adequately powered (Ioannidis et al., 2017), the selection model of Andrews & Kasy (2019), Stem-based method (Furukawa, 2019), and Endogenous kink model (Bom & Rachinger, 2019). I also plan to include p-uniform* or p-curve into my analysis (van Aert et al., 2016), since these tests are commonly used in psychology research but have not appeared in the economics research yet (to the best of my knowledge. Next, due to the fact that the collected studies will probably differ as in terms of data, methods, location, age, quality as well as other contexts, I need to properly examine and address the heterogeneity of the data.

The model uncertainty is intrinsic to any meta-analysis: many different variables capturing the design of the study are used to explain the effect studied. I cannot be sure beforehand; however, which variables are important and should be included in my regressions. If unimportant variables are kept in the model, the variance of the estimated parameters is likely to increase. Model averaging, such as its Bayesian variant, is a commonly applied tool in meta-analyses to deal with the model uncertainty. In my analysis, I want to focus on dilution prior applied in Bayesian setting (due to George, 2010), which treats for potential multicollinearity in data. Additionally, I would also like to apply several robustness checks, including different choices of model and parameter priors as well as Frequentist model averaging (Amini & Parmeter, 2012).

Expected Contribution The relationship between income inequality and happiness is essential for welfare policy decisions. It is, in fact, startling that there has been only one meta-analysis conducted in this area, so far (Ngamaba, 2017). In my thesis, I want to address several issues the previous meta-analysis does not touch upon. First, I would like to elaborate the literature review to a larger extent and provide an economic and econometric rationale behind several aspects of the study design. Second, I intend to enlarge the original dataset and collect more of the potentially important explanatory variables that could drive the estimated effects in the literature. Those might include different kinds of measurement approaches to income inequality and happiness, geographic differences, data aspects (frequency, dimension, length of the run, etc) and most importantly I would like to focus on the effects of country-level development. Third, I will investigate the potential presence of publication bias which was not accounted for in the previous meta-analysis. Last, I will use the novel methods to treat for model uncertainty and investigate the potential sources of heterogeneity systematically, using methods such as Bayesian model averaging or Frequentist model averaging.

Outline

1. Introduction: I will explain my motivation, contribution, and my main results.
2. Introducing the topic of inequality and happiness: I will briefly describe the topic of inequality and happiness.
3. Data: I will explain how I will collect estimates from the studies estimating the relationship between inequality and happiness (search query, inclusion criteria, etc.), provide the basic summary statistics, and try to cherry pick some interesting prima facie patterns in data.
4. Publication bias: I will briefly describe what publication bias is and why it could be present in this literature and use several linear and non-linear approaches to test for its presence. I will provide a short discussion based on the comparison of results from chapter 3 (simple means) and this chapter (means corrected for publication bias).
5. Heterogeneity: This chapter will have several important parts: 1) it will serve as a meticulous literature review of the topic (because in the beginning, I will describe why I chose the explanatory variables I chose and what the current academic literature tells us about these variables, 2) it will provide a short and concise introduction into the methods I am going to use to investigate the heterogeneity, and 3) it will provide a discussion of results that will come out of the examination of heterogeneity.
6. Best-practice estimate: Based on my results from chapter 5 (heterogeneity), I will analyse what the best-practice estimate should look like if researchers correct for publication bias and potential misspecifications.
7. Conclusion: I will summarize my results and provide implications for policy and future research. I will state potential drawbacks of my analysis, if any.

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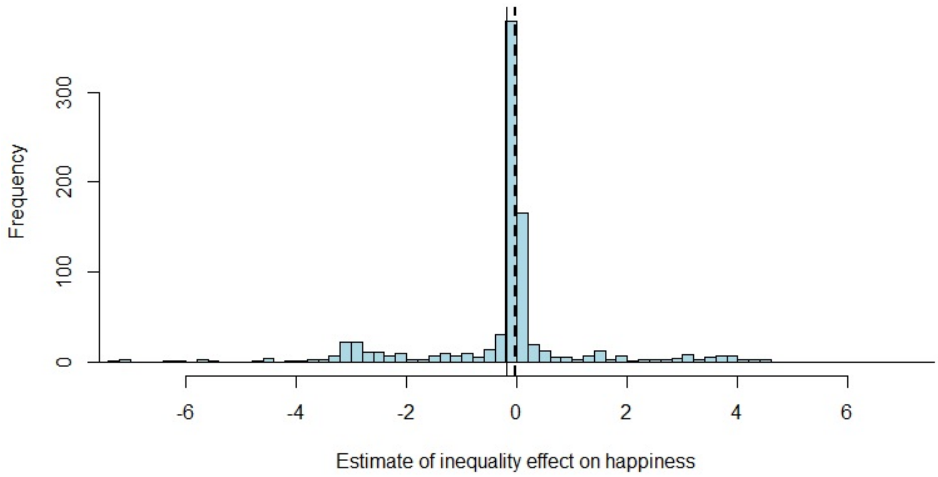
Chapter 1

Introduction

More than 70 years ago Duesenberry (1949) argued that people do not care as much about being poor as they care about feeling poor: relative not absolute wealth matters. Number of more recent studies show that income inequality is rather badly perceived in different contexts, causing economic and political issues (Mankiw 2013; Winship 2013; Wolbring *et al.* 2013; Pickett & Wilkinson 2015) and adverse negative societal outcomes (Delhey & Steckermeier 2019; Kelley & Evans 2017; Alesina *et al.* 2004; Oishi *et al.* 2011; Corak 2013; Choe 2008; Wilkinson & Pickett 2009; Easterly 2007). Moreover, income inequality has been always perceived as social evil, because it weakens social ties between individuals (Alesina *et al.* 2004; Delhey & Steckermeier 2019). It follows that any government that wants to make people happier pushes towards policies favoring social transfers, redistributing income from the rich to the poor.

Despite the popular consensus that income inequality has detrimental effects on people's happiness, the academic literature lacks any conclusion in this direction. Accordingly, to find one, the number of researchers interested in the relationship between income inequality and happiness has been recently increasing (Yan & Wen 2020; Kollamparambil 2020; Zhang & Churchill 2020; Ding *et al.* 2020). All previous reviews (Ferrer-i Carbonell & Ramos 2014; Schneider 2016; Ngamaba *et al.* 2018) testify to a large heterogeneity present in the literature on the relationship between income inequality and subjective well-being. Furthermore, they conclude that there could be certain aspects of data and methodology systematically driving the resulting reported income inequality effect on happiness and call for future research. Nevertheless, no one before has investigated the drivers of the relationship between income inequality and happiness systematically, as far as we are concerned.

Figure 1.1: Histogram of the estimate of inequality effect on happiness



Notes: The figure shows a histogram of the estimates of the income inequality effect on happiness reported by individual 53 studies. The vertical line represents the sample mean, the dashed vertical line represents the sample median.

As we mentioned, the respective literature on this topic is ambiguous. Some authors find the relationship to be negative (Alesina *et al.* 2004; Oishi *et al.* 2011; Delhey & Dragolov 2014; Schwarze & Härpfer 2007; Verme 2011), some positive (Helliwell & Huang 2008; Jiang *et al.* 2012; Berg & Veenhoven 2010; Clark 2003; Wang *et al.* 2015), and some do not find any (Senik 2004; Haller & Hadler 2006; Mikucka *et al.* 2017). The bird's eye view of the literature on the relationship between income inequality and happiness, presented in the Figure 1.1, shows that the effect sizes of income inequality on happiness vary substantially and do not provide a clear consensus. Although as can be apparent from the Figure 1.1, reporting negative relationship between income inequality and happiness prevails, supporting the popular view of income inequality negatively impacting people's happiness. To provide a clearer view of this relationship, we have collected 868 observations from 53 studies to investigate the heterogeneity in this literature.

The relationship between income inequality and happiness is essential for welfare policy decisions. It is startling that despite the ambiguity of the literature regarding the inequality-happiness link, there have been only a few reviews and one meta-analysis (Ferrer-i Carbonell & Ramos 2014; Schneider 2016; Ngamaba *et al.* 2018) conducted in this area. Firstly, since previous narrative reviews include up to 25 studies, we also contributed by the narrative review of the literature on the relationship between income inequality and happiness, which includes more than twice studies and also very recent ones. We reviewed both topics of happiness and income inequality separately and the concepts on which their complex relationship is based on. Most importantly, however, we contribute to the academic literature by being the first who address the heterogeneity of the relationship between income inequality and happiness complexly, including accounting for publication bias or using multivariate analysis. Since the first meta-analysis by Ngamaba *et al.* (2018) was based on 24 zero-order correlations from 24 studies and tested for pairwise differences between certain aspects of study design. Additionally, since the relationship between income inequality and happiness is very complex, we also contributed to the literature by collecting almost 80 potentially important explanatory variables that could drive the estimated effects in the literature for each of the 868 observations from 53 studies. Since researches accounts for various factors influencing the income inequality effect on happiness, such as trust (Oishi *et al.* 2011; Delhey & Dragolov 2014), health (Helliwell & Huang 2008; Wang *et al.* 2015), mobility (Alesina *et al.* 2004; Graafland & Lous 2018), GDP or wealth (Berg & Veenhoven 2010; Engelbrecht 2009) and many others. We accounted for model uncertainty using model averaging techniques and discussed the heterogeneity behind the estimates thoroughly, paying particular attention to publication bias.

Publication bias is the tendency of researchers to prefer not reporting non-intentionally or intentionally all results but only the statistically significant results or results supporting previous findings or underlying theory, as discussed by Stanley (2005); Doucouliagos & Stanley (2013); Gechert *et al.* (2021); Havranek & Irsova (2017). It is essential to account for publication bias in the literature because, since as shown by Ioannidis *et al.* (2017) in economics, the mean reported coefficient could be exaggerated twofold. We decided to address the publication bias in the respective literature since no one has done so before, and the general public perceives income inequality as detrimental to happiness. In our meta-analysis, we perform the most recent and state-of-the-art test for detecting publication bias. We showed that publication bias is present in the literature on the relationship between income inequality and happiness but that it is created by the selection of individual studies.

Publication bias survives the unweighted sample even if we account for 62 features of the study design, for which we use the Bayesian and Frequentist model averaging, accompanied by frequentist check. We found out that both income inequality and subjective well-being specifications systematically drive the estimates of the effect. We show that using happiness as a measure of subjective well-being is linked with more positive income inequality effects, compared to using life satisfaction. Furthermore, using income inequality measure based on net and gross income is associated with more negative effects, compared to one using other income groups like expenditure and consumption. The relationship between income inequality and subjective well-being is also significantly systematically driven by data and publication characteristics, such as data midpoint, data length, publication year, and impact factor. Most importantly, our results also reveal significant geographical and country variations, implying that income inequality has a more negative effect on happiness in the United States, Europe, and China. Additionally, the inclusion of perceived trust in people or health status variable is systematically associated with a more positive effect of income inequality on subjective well-being. Contrarily, the inclusion of individual's religious and employment status is connected to a more negative effect. Alternatively, we found the inclusion of some macroeconomic variables as GDP significant and associated with a more positive effect.

The thesis is structured as follows. Chapter 2 presents the concept of happiness and income inequality, the theories thorough which are linked, and an introduction to the literature review on the relationship between income inequality and happiness, on which we will focus throughout this thesis. In Chapter 3, we describe our data collection process as well as provide a summary statistics of the data set. Chapter 4 examines possibility of publication bias in literature, applies and describes several techniques used for its investigation, and discusses its results. In Chapter 5, we analyze the heterogeneity present in the literature concerning the relationship between subjective well-being and income inequality in detail, describe methods used to investigate the heterogeneity, and provide a comprehensive discussion of the findings. In Chapter 6, we summarize the main concluding remarks. In the Appendix, we provide additional materials, such as figures and tables.

Chapter 2

On the happiness, inequality, and their relationship

2.1 Happiness

Although happiness has always been one of the most widely discussed topics throughout history, it has recently gained in importance across societies worldwide. Since in the past, people used to focus more on becoming rich because they believed chasing wealth would bring them happiness. All around the world, individuals' wealth has been rising and poverty has been reducing alongside a growing global middle-class (Neckerman & Torche 2007; Desai & Kharas 2017). Nevertheless, people's happiness levels around the world are stagnating and are not as high as they should be if they followed patterns of wealth, education, or several life conditions (Pinker 2018). Many studies proved that wealth does not make people happier nor more satisfied with their lives in the long-term (Easterlin 1973; 1995; 2001; Ferrer-i Carbonell 2005; Wolbring *et al.* 2013; Clark *et al.* 2008). An excellent example provides research by Brickman *et al.* (1978), who proved that people one year after winning the lottery and one year after getting paraplegics are on average the same happy.

Accordingly, the key question nowadays is how to achieve happiness because humankind is no closer to finding happiness than it was decades ago despite all the progress made around the world. Even though people have much more things to be happy for as time passes, they seem to criticize and complain more than ever in history. As also summarized by Mueller (2001): "People seem simply to have taken the remarkable economic improvement in stride and have deftly found new concerns to get upset about." Throughout history, the perception of happiness progressively changed, although the aim of achieving happiness among societies prevailed and has been considered the highest human mission (Kelley & Evans 2017). The search for happiness began in Ancient Greece with Aristotle's ideal of "eudaemonia" meaning good spirit, and meaningfulness (Bok 2010). Although meaningfulness might differ from happiness since many things can make people unhappy in the short term, but make them fulfilled over the lifetime, as raising a child (McMahon 2006). However, we decided to use happiness measure because of being more present-oriented, so more sensitive to various factors, and has higher number of data-sets and studies (Baumeister *et al.* 2013). Additionally, as mentioned by (Bok 2010), the search for happiness continued during the Roman Empire, where happiness implied divine favor, and for Christians, it was synonymous with God. McMahon (2006) argues that our modern search for happiness is influenced by ethical normative theories from the 19th and 20th century, as by Utilitarianism, with an aim to eliminate misery and spread happiness to all.

The search for happiness in the modern form continues to this date, and its searching is becoming more and more popular. However, instead of generating new forms of pleasure, it generates new forms of pain for today's society. Thus, the biggest question now is how this unhealthy chase can be stopped and how can at least a slight increase in happiness been spread around the world. The most obvious answer is with the help of world leaders and governments, but how? One of the most apparent choices that could influence people's happiness and that government can influence is the level of income inequality, more precisely level of income redistribution from rich to poor. In later sub-chapters, we will discuss income inequality in more detail. Next, we present also other determinants of happiness widely discussed in the literature.

In 1973, the economist Richard Easterlin identified a paradox that has been later named after him (Easterlin 1973; 1995; 2001). It stated that more affluent people are happier while comparing citizens within a country not across countries, and that people did not seem to get happier with their country's enrichment over time. Two psychological theories can explain the Easterlin paradox. First, the hedonic treadmill theory, according to which people adjust to changes in their fortunes and go back to a genetically determined baseline (Brickman & Campbell 1971). Second, the theory of social comparison, which states that people's happiness is defined by how good they think they're doing compared to their peers. Accordingly, when the country becomes wealthier, no one is likely to be happier, and it could also make things worse if the country becomes more unequal (Festinger 1954).

Therefore the social comparison theory is also one of the main theories explaining the importance of the income inequality effect on happiness, on which we will later elaborate in-depth. In history, many studies proved that relative income influences happiness significantly, and even more than absolute income (Ball & Chernova 2008; Easterlin 1973; 1995; 2001; Ferrer-i Carbonell 2005; Wolbring *et al.* 2013; Clark *et al.* 2008; Kelley & Evans 2017). On the other hand, several newer studies, such as by Becker *et al.* (2008); Helliwell *et al.* (2016); Inglehart *et al.* (2008); Sacks *et al.* (2012); Stevenson & Wolfers (2008), brings new evidence and disprove the Easterlin paradox theory. They show that richer people are happier both across and within countries, but also that people seem to get happier as their countries get richer (Sacks *et al.* 2012).

Generally, not only income influences happiness. Many researchers, such as Inglehart *et al.* (2008); Helliwell *et al.* (2016); Veenhoven (2010), showed that nations are happier if their citizens are in better health or feel freedom choosing what to do with their lives. Researchers as Sanfey & Teksoz (2007); Oshio & Kobayashi (2010); Ding *et al.* (2020); Tomioka & Ohtake (2004), also found that females are happier than males and that the age variable follows a familiar U-shape pattern with the lowest level at approximately 45 years old. Similarly, Alesina *et al.* (2004) reported that females seem happier than males and that the members of a traditionally discriminated minority are less happy. Additionally, most researchers as Ding *et al.* (2020); Yan & Wen (2020); Tomioka & Ohtake (2004), confirmed that individuals who are married, more educated, religious, or with higher trust in people reported higher subjective well-being.

People's happiness can also be influenced by culture and geographical regions. For example, according to Inglehart *et al.* (2008), citizens of Latin American countries are happier than they ought to be given their income. Additionally, several researchers proved that Americans belong among the happiest nations. Other researchers as Yan & Wen (2020) or Tella *et al.* (2003) focused on macroeconomic variables and confirmed that a higher inflation rate causes lower subjective well-being. Alternatively, Haller & Hadler (2006) found that the gross national product has a significant positive effect on happiness.

In history, the critic's distrust in the possibility that happiness can even be measured occurred. Since according to philosophers and social scientists, happiness is not a single dimension but rather a complex and multi-dimensional concept (Wang *et al.* 2015). Happiness and life satisfaction are truly neither known personal fact nor verifiable experience, but rather a retrospective judgment which can be measured only by asking (Pinker 2018). Thus, the reliability of the happiness and life satisfaction questions can be limited by different contexts and respondent's current moods. Nevertheless, these effects are not undoubtedly grounds for dismissing the method generally, since, in representative population samples, the idiosyncratic effects of irrelevant events are likely to average out (Kahneman & Krueger 2006). Additionally, even though the current context and mood may cause fluctuations in people's responses, a significant correlation between the repeated subjective well-being measures suggests that the data might be accurate enough for large numbers of purposes.

Generally, the difference between happiness and life satisfaction is perceived to be mild or any (Ferrer-i Carbonell & Ramos 2014; Alesina *et al.* 2004). Life satisfaction measure started to be used since the word "happy" expresses differently across languages. We will illustrate the concrete distinction between happiness- and life satisfaction-oriented questions using the two following questions from the Euro-Barometer Survey Series. We can see the meaning of the happiness-oriented question: "Taking all things together, would you say you're very happy, fairly happy, or not too happy these days?", is not far from the life satisfaction-oriented question: "On the whole, are you very satisfied, fairly satisfied, not very satisfied or not at all satisfied with the life you lead?" (Alesina *et al.* 2004).

The measure gained by answering happiness and life satisfaction questions is generally called subjective well-being (SWB). Since these questions, as shown above, are both very subjective and about an individual's well-being. Subjective well-being is just a proxy for an individual's utility. In the literature, it is the measure most often used to estimate the relationship between inequality and individual's well-being (Ferrer-i Carbonell & Ramos 2014; Kahneman & Krueger 2006). Overall, the vast majority of researchers use terms subjective well-being (SWB), happiness, and life satisfaction interchangeably (Frey *et al.* 2018; Alesina *et al.* 2004; Tella *et al.* 2003). In line with the relevant literature, we also decided to follow this trend in this meta-analysis. The main motive behind whether to choose happiness or life satisfaction questions is usually data availability. However, to take happiness and life satisfaction questions and their answers as a proxy measure of utility, two principal assumptions need to be imposed, as mentioned by Ferrer-i Carbonell & Ramos (2014). Firstly, the questioned individuals are capable and willing to give a meaningful answer, which is a positive monotonic transformation of utility. And secondly, that the answers to happiness and life satisfaction questions need to be compared in a meaningful way, meaning the answers to these subjective questions need to be comparable inter-personally that at the ordinal or cardinal level.

These assumptions can be supported by satisfactory and extensive empirical evidence, which presents a consistent correlation between the answer to subjective well-being question and some objective measure of well-being, such as for example the amount of smiling, or changes in facial muscles during the questionnaire interview (Sandvik *et al.* 2009; Kahneman *et al.* 1999; Ekman *et al.* 1990). Moreover, many researchers also present links between the subjective well-being and individuals' behaviour, such as the negative correlation of the happiness data and measures of heart rate or blood pressure as a response to stress (Shedler *et al.* 1993). Emerging stand of literature presents extensive evidence on the reliability of SWB measures so that there is confidence in measuring individuals' subjective well-being meaningfully (Clark *et al.* 2008; Frey & Stutzer 2010; Layard 2010). In recent history, the answers to subjective well-being questions regarding life satisfaction or happiness have been already used by many researchers to examine various relationships between SWB and individuals' characteristics (such as income, health or employment status), or regional characteristics (such as GDP and inflation), next to income inequality (Alesina *et al.* 2004; Ferrer-i Carbonell & Ramos 2014).

Additionally, the approaches to measuring the subjective well-being variable can also vary in assuming ordinality or cardinality. Over the last 70 years, the ordinal utility concept prevailed in economics. However, economists and psychologists started to worry that preferences may not a brilliant guide of the well-being related to the consequences of choices (Dolan *et al.* 2008). The boom of the happiness studies happening in the past 20 years began much sooner by the work of Easterlin (1973) and most of these happiness studies generally use classical utilitarian concept. From a theoretical perspective, the distinction between cardinal and ordinal happiness is critical. In the latter case, there is no particular meaning in the difference between the happiness answers. The ordinal approach to happiness is linked to the behaviorist preference perspective with the measurement assumption that utility cannot be measured nor compared across people. On the other hand, the cardinal approach is associated with the utilitarian, hedonic appraisal perspective with the measurement assumption that utility can be measured and compared across people (Hirschauer *et al.* 2014). Nowadays, the researchers still may vary in assuming cardinality of the subjective well-being measure, such as Jiang *et al.* (2012), or ordinality, such as Ding *et al.* (2020), resulting in estimating the happiness equation using the different econometric methods. Luckily, Ferrer-i Carbonell & Frijters (2004) have proven that there are only slight differences between results assuming cardinal or ordinal SWB measure.

2.2 Income inequality

In most Western countries, income inequality has undoubtedly risen since the 1990s, especially in the United States compared to other developed countries in Europe (Piketty & Saez 2014). The income inequality has increased particularly between the very richest and the rest of the population (McCall & Percheski 2010). Generally, the increasing income inequality is a serious problem and has been a major concern around the world (Nguyen *et al.* 2015). For example Kelley & Evans (2017) describes income inequality as "a source of political conflict for centuries," as well as that it is nowadays "widely feared as a pernicious side effect of economic progress." Also, Alesina *et al.* (2004) has described income inequality as a "social evil." Additionally, the formal president Barack Obama aptly referred to income inequality as "the defining issue of our time" (Nguyen *et al.* 2015). Alternatively, Deaton (2013) claims: "A better world makes for a world of differences; escapes make for inequality."

Income inequality is, throughout the literature, automatically perceived very negatively, possibly because of its pronounced numerous negative consequences (Kelley & Evans 2017). Evidence of the detrimental impact of income inequality on society is present in the literature throughout the fields. Researchers showed that income inequality is positively linked with crime (Choe 2008; Fajnzylber *et al.* 2002), and oppositely negatively connected to health (Kaplan *et al.* 1996; Easterly 2007; Pickett & Wilkinson 2010), perceived trust (Knack & Keefer 1997; Pickett & Wilkinson 2010) or social mobility (Corak

2013; Wilkinson & Pickett 2009). Additionally, income inequality can affects several kinds of economic and political dysfunctions, such as financial instability, economic stagnation, or underdevelopment (Mankiw 2013; Winship 2013; Pickett & Wilkinson 2015). Alternatively, income inequality is associated with several other negative consequences such as significant social dysfunction (Wilkinson & Pickett 2009), higher rates of obesity or teenage pregnancy (Pickett & Wilkinson 2010), or higher mortality (Kawachi *et al.* 1997). Also, based on research in behavioral economics, several researchers confirmed that females are more inequality-averse than males (Andreoni & Vesterlund 2001; Oshio & Kobayashi 2011).

Overall, even though income inequality among nations is decreasing, individuals' wealth has been rising together with the proportion of their wealth in modern societies dedicated to helping the less well-off (Neckerman & Torche 2007). As well as globalization and technology progress helped to take many people out of poverty and increase the global middle-class (Desai & Kharas 2017). Despite these and many more improvements in our society, the people's happiness has not increased. While analyzing the relationship between happiness and income inequality to address this situation, various factors need to be controlled. During the analysis, researchers need to consider that the economically egalitarian countries (such as Sweden or France) differ significantly from the non-egalitarian countries (such as Brazil or South Africa) by other factors than just income inequality (such as GDP or culture). Therefore, we need to be aware that just a simple correlation between happiness and income inequality might demonstrate that there are many reasons why living in a country with lower income inequality is better than in a country with high-income inequality.

In literature, there exist several measures of income inequality, such as the percentage of total income owned by the top quartile of the income distribution, the percentile ratios (as the 90/10 ratio), or one-number indexes such as Theil or Atkinson indexes. Nevertheless, the most popular measure for analyzing income inequality and its many effects is generally the Gini index (Kelley & Evans 2017). The Gini coefficient is a number ranging from zero to one calculated based on the Lorenz curve concept. When it is equal to zero, the society is completely egalitarian, meaning that each individual has the same income. When it is equal to one, the society is contrarily perfectly unequal, meaning that all income is owned by one individual (De Maio 2007). In the real world, the Gini coefficient generally usually varies between 0.24 and 0.62 (OECD 2020). The countries with one of the most egalitarian income distributions are Scandinavian countries, the Czech Republic, or the Slovak Republic. Contrarily, the countries with highly unequal distribution are South Africa or other countries in Africa or Latin America (OECD 2020). In the United States' history, the Gini coefficient for household income increased from 0.43 in 1990 to 0.48 in 2019 (Statista 2021).

In detail, the Gini coefficients curves correspond to the Kuznets curve, since it shows that the income inequality increased steadily after the industrial revolution until the 1980s, from which it started to fall (Kuznets 1955). Kuznets curve represents a well-known hypothesis by Kuznets (1955) presuming that as countries get wealthier, they ought to become less equal, confirmed by the data indicating that Gini coefficient, creating a hypothetical arc of inequality over time reassembling an inverted-U (Kelley & Evans 2017). Despite the displeasure prevailing across societies connected to income inequality increase in developed countries, the global income inequality around the world is decreasing (Deaton 2013).

2.3 Linking inequality to happiness

After introducing both happiness and income inequality topics, we would like to elaborate on their relationship. From the psychological perspective of an individual, as mentioned by Ferrer-i Carbonell & Ramos (2014), three following situations can arise. Firstly, since most people are self-interested, their positive or negative relationship with income inequality depends on the positive probability that they could benefit or lose from it. Secondly, when people are not self-centred but genuinely care for other people, their aversion or liking of income inequality affecting their well-being can arise from how well surrounding people are doing. Finally, how positive or negative is the relationship between happiness and income inequality can also influence individual citizens' subjective relative concerns.

Even in recent literature regarding the determinants of happiness, it remains unclear exactly how income inequality affects subjective well-being, as mentioned by Jiang *et al.* (2012). Nevertheless, we would like to present the most important theories using which researchers could explain the effect of income inequality on subjective well-being. As we have mentioned before, one of the main theories explaining the income inequality effect on happiness is called social comparison theory by Festinger (1954). The social comparison theory claims that when individuals deal with income inequality, their happiness depends on comparing their socio-economic status with close others. This theory is widely discussed in the literature since it is also in line with the previously explained Easterlin paradox. The social comparison theory could be interpreted also as comparing the present level of income inequality to the one they have experienced in the past. The social comparison theory is also called a theory of reference group (Merton & Kitt 1950) with the difference that in the theory of social comparison, the reference groups play a much larger role in self-evaluations in unstable conditions (Kelley & Evans 2017).

Similarly, the theory that individuals earning less are likely to be less happy than those earning more in a specific referential group is discussed in economics as the relative income hypothesis by Duesenberry (1949). Correspondingly, the relative deprivation theory also states that the negative effect of income inequality on individual's happiness arises when an individual is frustrated and deprived if others are better-off (Verme 2011). This theory concerning the relationship between well-being and income inequality has been proven by Alesina *et al.* (2004); Oshio & Kobayashi (2011); Schwarze & Härpfer (2007); Hagerty (2000). Also, Schneider (2019) underlines the importance of relative deprivation theory for explaining income inequality's effect on SWB. Alternatively, Yu *et al.* (2019) found the relative deprivation theory relevant for migrants in the lowest socio-economic classes in China. Additionally, Wu & Li (2017) also supported the relative deprivation theory, even after controlling for both individual and aggregate characteristics inclusive of the rate of GDP growth.

A closely related theory of status anxiety sees the negative income inequality effect on individuals' happiness because individuals always compare themselves upward. Therefore the more wealthy the elite in society is, the lower happiness of the rest of the individuals, as confirmed by Layte (2012) and Wilkinson & Pickett (2009). Similarly, spirit level theory by Pickett & Wilkinson (2010) primarily shows how income inequality has negative effects on various life aspects. Pickett & Wilkinson (2010) proves that income inequality affects negatively many fundamental determinants of our lives, such as quality of social relations or perceived trust in people, both closely related to an individual's well-being.

The next crucial theory concerning the relationship between happiness and income inequality is called the tunnel effect theory. The tunnel effect theory by Hirschman & Rothschild (1973) is based on perceiving higher income inequality as a sign of possibly higher income, thus a more promising future, which is likely to increase happiness. Hirschman & Rothschild (1973) demonstrates the tunnel effect theory using an example of getting stuck in a traffic jam in a two-lane tunnel, both lanes in the same direction. If the other lane starts to move, then even if your lane is not moving at the moment, your expectation about moving soon will bring you happiness. On the other hand, if you become stuck for a long time, negative emotions can arise, suggesting that long-term income inequality negatively affects well-being. Therefore, the tunnel effect theory is connected to the concept of perceived social mobility (Zhang & Churchill 2020).

In general, the tunnel effect theory predicts the opposite relationship of happiness and income inequality to the relative deprivation theory (Esping-Andersen & Nedoluzhko 2017). Many researchers studying the relationship between income inequality and subjective well-being confirmed the tunnel effect theory, such as Grosfeld & Senik (2010) claiming that this effect is relatively typical for transition countries, at least at the start of the transition. Also Clark (2003) and Knight *et al.* (2009), supported the tunnel effect theory since they show a significant positive effect of income inequality on well-being supported by upward mobility. Zhang & Churchill (2020) supported both the relative deprivation hypothesis suggesting a negative effect of income inequality on subjective well-being and also the tunnel effect theory since the inequality in China is persistent despite the significant economic growth.

Another theory possibly explaining the happiness-inequality link is called the adaptation-level theory, suggesting that inequality changes over time might influence well-being before the individual starts to adapt (Clark *et al.* 2008). The adaptation-level theory is closely related to the theory of hedonic adaptation by Brickman & Campbell (1971). Both theories suggest that even if the lower incomes rise across the world so that the income inequality diminishes, an individual still tends to adapt in the long run to better conditions. The individual is likely to increase the evaluative standards, causing that his subjective well-being is not expected to rise simultaneously. In psychology, there also exists a syndrome called inequality aversion, which also concerns the happiness-income inequality link and claims that individuals would prefer any unexpected profit to be divided evenly among various participants (Clark 2003; Schwarze & Härpfer 2007). Nevertheless, recent articles deny this syndrome by saying that individuals prefer unequal distributions as long as individuals feel that the allocation is fair. According to them, the desire to spread the wealth does not hold, in the case when the unexpected profit goes to individuals who truly deserve it as the worker who works the hardest (Starmans *et al.* 2017).

The first empirical study in history investigating the relationship between income inequality and happiness was written in 1976 by Morawetz et al., who investigated the two Israeli Kibbutz communities with the most diverse income structures and analyzed the well-being of inhabitants of those communities. The results were that members of the Anisos Kibutz with a more hierarchical income structure were less happy than members of the Isos Kibutz with a strongly egalitarian social structure (Morawetz 1977). Although, these findings proved that the more equal the income distribution is, the higher the subjective well-being. The explanatory power of these empirical findings is limited because Morawetz (1977) studied just two commodities, so the difference in the individual's happiness could be caused by other unobserved characteristics of these two Kibutz.

Therefore, further research was needed in order to discover if income inequality is beneficial or detrimental to an individual's well-being. Luckily, many researchers conducted numerous studies on this topic throughout the past more than 40 years. Some of them focus explicitly on the contextual relationship between income inequality and happiness, while other address income inequality as one of few contextual influences on the well-being of individuals. Unfortunately, the studies' findings are diverse and sometimes contradictory. Researchers disagree on whether individuals living in an equal environment report higher or lower well-being than those living in unequal societies. In conclusion, some studies present positive effect of income inequality on individual's well-being (Berg & Veenhoven 2010; Clark 2003; Helliwell & Huang 2008; Rözer & Kraaykamp 2013; Tomioka & Ohtake 2004); some negative effects (Alesina *et al.* 2004; Delhey & Dragolov 2014; Oishi *et al.* 2011; Du *et al.* 2019; Zhang & Churchill 2020; Yan & Wen 2020; Yu *et al.* 2019; Oshio & Kobayashi 2011; Ravazzini & Chávez-Juárez 2018), and orhers no significant results (Senik 2004; Haller & Hadler 2006; Mikucka *et al.* 2017; Beja 2014).

As previously mentioned, the studies analyzing the link between income inequality and well-being are very heterogeneous. Some use cross-country comparisons, however, the majority analyzes this relationship with regards to specific geographical regions. Such as Senik (2004) found the relationship between happiness and income inequality in Russia insignificant. Or Grosfeld & Senik (2010) found a positive relationship between income inequality and life satisfaction in transitioning Poland. Similarly, Helliwell & Huang (2008) also observed a positive effect of income inequality on life satisfaction in Latin America. Alternatively, many other country-specific studies exist, as well as cross-country studies diversifying developed and developing parts of the world and many others, as we will describe later in the next chapters.

The relationship between subjective well-being and income inequality could also be influenced by macroeconomic effects such as the country's economic prosperity, governance quality, or unemployment. For example, Layte (2012) observes that income inequality decreases happiness in countries with low or medium GDP less strongly than in countries with high GDP. Alternatively, Helliwell & Huang (2008) reported that there is a positive effect of income inequality on the well-being in badly-governed countries, but no significant effect in well-governed countries. Or Berg & Veenhoven (2010) found a negative correlation between life satisfaction and income inequality, but which becomes positive if GDP is controlled for. The relationship between income inequality and well-being can also be affected by personal characteristics such as gender, age, race, employment status, income, or perceived trust and mobility. For example, Blanchflower & Oswald (2003) found out that income inequality has a negative effect on the subjective well-being of American women. Similarly, Oshio & Kobayashi (2011) show that income inequality has a more negative effect on happiness for a female subgroup than for the male. Or Alesina *et al.* (2004) reported that in Europe, the happiness of poor and left-wing individuals is affected by income inequality negatively, but in the USA is not affected at all.

To show even more the vast heterogeneity present in the literature regarding the income inequality effect on happiness, we present also diverse findings of following researchers. For example, Kelley & Evans (2017) in their study of 200,000 people in 68 societies over three decades, reported that income inequality generally affects happiness very negatively when they controlled for GDP per capita, age, sex, education, marital status, as well as religious attendance.

Roth *et al.* (2017), based on data from the German Socio-Economic Panel Study for the years 1984 to 2012, found that the national-level income inequality has a negative effect on average life satisfaction, controlling for regional dummies, GDP, unemployment rate, age, gender, and employment status. Furthermore, also Graafland & Lous (2018) using panel analysis on a sample of 21 OECD countries, concludes that income inequality is found to have a negative effect on life satisfaction controlling for freedom variable. Alternatively, Katic & Ingram (2018) found a positive relationship between income inequality and SWB focusing of effect of perceived fairness, social comparison, as well as perceived social mobility. Or, according to Oishi *et al.* (2011) it is the lack of trust and perceived unfairness that causes that income inequality to have a negative effect on happiness.

Generally, it cannot be concluded how income inequality affects the individual's well-being nor precisely which control variables moderates the relationship between income inequality and SWB in the larger context. As mentioned by Schneider (2016), it is not clear which institutional arrangements, economic, sociological, or cultural conditions compensate for or changes the positive or negative effects of income inequality on happiness. In history, two qualitative literature reviews were written on the topic of income inequality and happiness by Ferrer-i Carbonell & Ramos (2014), and Schneider (2016), as well as one meta-analysis by Ngamaba *et al.* (2018). The meta-analysis by Ngamaba *et al.* (2018) is based on 24 zero-order correlations from 24 studies, concludes that the link between income inequality and subjective well-being is complex, however do not study the heterogeneity of relevant literature in-depth. Thus, the vast complexity of this relationship should be elaborated on much more comprehensively, which we aim to do in our meta-analysis.

Chapter 3

Data and its collection

To conduct a meta-analysis, we need to construct a data set consisting of the necessary data from all the studies relevant to the specific topic of meta-analysis. In our case, the topic is the relationship between income inequality and subjective well-being (SWB). The first step is to collect all studies relevant to the topic but include into the meta-analysis only studies satisfying the selection criteria. Selection criteria need to be set reasonably. Since when they are too strict, the possibility of finding suitable studies is low, as well as the probability of looking at the selected topic from a broader picture. Oppositely, when they are loose, the obtained studies are likely to be too heterogeneous, and the results too general.

The principal selection criteria for the inclusion of the study into this meta-analysis are:

1. Study uses quantitative methods.
2. Study provides a defined coefficient regarding the association between income inequality and SWB, using SWB as a dependent variable.
3. The coefficients are captured by standard errors, t-statistic, p-values, or other statistics from which it can be computed.
4. Study includes a measure of SWB, in the form of responses to the questions considering happiness or life satisfaction of the respondent.
5. Study uses the Gini index as a measure of income inequality.

The search strategy for the meta-analysis was conducted through Google Scholar, since it is superior to all other databases thanks to its powerful full-text search and the fact that it does not discriminate as to the research field. As a search query for Google Scholar, we use the following keywords: happiness, life satisfaction, subjective well-being, income inequality, income distribution, Gini. We went through as many studies in the search query as possible and their abstracts, in order to determine the individual study's relevance. If we saw from the abstract a slight possibility that the paper could be relevant, we inspected the paper in-depth. We have pursued this method for most of the studies. Additionally, later on, while going through the selected relevant studies to collect the data, we also performed a snowballing technique, which uses the previously collected primary studies and their references to expand the search and get more relevant studies. Our data search took place until the end of February 2021. The list of studies included in the meta-analysis is presented in the Table 3.1.

Table 3.1: Studies included in the meta-analysis

	Author (Year)	
Alesina *et al.* (2004)	Beja (2014)	Berg & Veenhoven (2010)
Carr (2013)	Clark (2003)	Delhey & Dragolov (2014)
Ding *et al.* (2020)	Du *et al.* (2019)	Eksi & Kaya (2017)
Engelbrecht (2009)	Fischer (2009)	Grosfeld & Senik (2010)
Gruen *et al.* (2005)	Gruen & Klasen (2012)	Hagerty (2000)
Hajdu & Hajdu (2014)	Haller & Hadler (2006)	Helliwell & Huang (2008)
Huang (2019)	Cheung (2016)	Cheung (2018)
Cheung & Lucas (2016)	Jiang *et al.* (2012)	Joshanloo&Weijers(2016)
Katic & Ingram (2018)	Kelley & Evans (2017)	Kim (2011)
Kollamparambil (2020)	Livani (2017)	Mikucka *et al.* (2017)
Muffels *et al.* (2012)	Ng & Diener (2019)	Nguyen *et al.* (2015)
Tomioka & Ohtake (2004)	Oishi *et al.* (2011)	Oishi & Kesebir (2015)
Oshio & Kobayashi (2010)	Oshio&Kobayashi(2011)	Ravazzini &
Rodriguez-Pose &	Roth *et al.* (2017)	& Chavez-Juarez (2018)
& Maslauskaite (2012)	Senik (2004)	Schalembier (2019)
Sanfey & Teksoz (2007)	Schröder (2018)	Schwarze&Harpfer(2007)
Schneider (2019)	Wang *et al.* (2015)	Wu & Li (2017)
Verme (2011)	Yu *et al.* (2019)	Yan & Wen (2020)
Zhang & Churchill (2020)		

In total, we managed to collect data from 53 studies, from which we gathered 868 estimates of the income inequality effect on subjective well-being. We omitted collecting estimates from several studies which did not report precise statistics from which standard errors can be calculated since they are needed for recent meta-analysis methods. While going through studies, we also collected any possible additional characteristics that are likely to explain the heterogeneity among the estimates, as presented later in the Table 5.1. We collected estimates from both published and unpublished studies. In particular, 46 out of the 53 primary studies are published in journals, three are working papers, two are a part of dissertations, and one is a technical report.

The most recent study in our meta-analysis was published in 2020. In particular, four studies out of 53 included were published in 2020, namely by Ding *et al.* (2020); Yan & Wen (2020); Zhang & Churchill (2020); Kollamparambil (2020). Furthermore, the oldest study was published in 2000 (Hagerty 2000). Thus, our 53 studies cover 20 years of recent research in that area of literature. According to Google Scholar and its number of citations of the study, the most cited study is Alesina *et al.* (2004) with 2437 citations. Next, the studies with the highest number of citations are Haller & Hadler (2006); Oishi *et al.* (2011); Senik (2004) with 731, 664, and 609 citations, respectively. Out of 868 estimates of the relationship between happiness and income inequality, 338 estimates are negative and statistically significant, 161 are positive and statistically significant, 231 estimates are negative but insignificant, and 126 are positive but insignificant.

The general empirical approach, which the relevant literature investigating the relationship between income inequality and happiness uses for estimating the effect of income inequality on subjective well-being (Ferrer-i Carbonell & Ramos 2014; Alesina *et al.* 2004; Verme 2011), is following:

$$\mathrm{SWB}_{irt} = \alpha + \beta_1 \mathrm{INEQ}_{rt} + \beta_2\ \mathrm{MICRO}_{irt} + \beta_3\ \mathrm{MACRO}_{rt} + T_t + R_r + \epsilon_{irt} \quad (3.1)$$

The dependent variable denoted as SWB_{irt}, represents happiness or life satisfaction, generally cumulatively called subjective well-being (SWB), and subscript i indicates an individual in a region or country r and time t. Primarily to estimate the impact of the income inequality on SWB, the equation includes the income inequality measure denoted as INEQ_{rt}, which can differ across region as well as time if panel data are used. Another essential variable is the set of individual characteristics, denoted as MICRO_{it}. It comprises variables such as gender, age, religion, race, health, education, employment status, income, residential status, marital status, perceived mobility, or perceived trust in people. Next, variable MACRO_{st} is also important for the relationship between income inequality and SWB, since it represents a set of characteristics aggregated at the country-level, regional-level, or possibly provincial-level depending on the type of study. It comprises variables such as GDP, income, unemployment and inflation rate, freedom, or governmental quality. Many researchers also include dummy variables (R_r) for the cross-sectional units, which could be region or country according to the type of study. Additionally, many researchers include time dummy variable (T_t), such as each year, or possibly some particular studies also denoting data wave dummy, ϵ_{it} being the usual error term.

To provide further insight into the data, we need to mention that studies estimating the income inequality effect on subjective well-being differ in using different income inequality and subjective well-being measures. Throughout the empirical literature examining the relationship between income inequality and subjective well-being, various income inequality measures have been used, such as top quartiles, percentile ratios, or Theil or Atkinson indexes. For example Blanchflower & Oswald (2003), Ott (2005) used income percentile ratios, or Hagerty (2000), Tomes (1986) used just simply minimum and maximum income, or the skewness. Nevertheless, these studies represent only a few exceptions we ran across during the data collection process. Indeed, the vast majority of the literature concerning the relationship between income inequality and subjective well-being uses the Gini coefficient as an income inequality measure of country or region (Ferrer-i Carbonell & Ramos 2014). Hence, as we mentioned previously, only studies including the Gini coefficients were included.

The focus on the Gini coefficients as income inequality measure is caused mainly because of data availability issues, as mentioned by Gruen & Klasen (2012). Since data on the Gini coefficients are more widely available than data on quintile shares, and on the Atkinson index (De Maio 2007). The availability of the Gini coefficients has even ameliorated significantly over the last two decades (Gruen & Klasen 2012). Not only can researchers choose from various data sources, but some data sources also offer multiple Gini coefficients for a given year and region. Additionally to the Gini coefficients, Schwarze & Härpfer (2007) also uses alternative measures of income inequality such as Atkinson and Theil measure. Also, Wang *et al.* (2015) does not rely on only one measure of income inequality and next to the Gini index uses the Theil index and the income share of the richest 50%. Their robust results across income inequality measures, however, provide consistent evidence supporting using the Gini coefficient as the only measure of the income inequality effect on happiness.

Nevertheless, even the Gini coefficients can differ since they could be based on income with or without taxes and transfers or other income groups, such as expenditure data. As mentioned by Verme (2011), the Gini coefficients based on expenses or consumption are typically lower than those based on income. Unfortunately, not all studies report details on their Gini coefficients. As a result, we needed to search for it by looking deeper into the used data set. Generally, some databases include only the Gini coefficients based on specific income groups such as disposable income: the SWIID, the Australian's Hilda, or the Eurostat. Nevertheless, many data sets do not systematically distinguish between the types of income used in their calculations of the Gini coefficients: the WIID, the World Bank, or the Deininger-Square. In these cases, when the researchers themselves do not specify which income group they have chosen for their study, we are not able to obtain this information. Overall, in the literature on the happiness-income inequality link, the most frequently used Gini coefficient is based on disposable also called net incomes.

The Gini coefficients also may use different reference units, such as household or family, but only a few researchers also mentioned this information in their studies, as mentioned by Gruen & Klasen (2012). Additionally, since the Gini coefficients can be calculated not only for countries but also for various regions or other particular reference groups, it is important to diversify between country-level and regional-level Gini. Some researchers such as Katic & Ingram (2018) or Verme (2011), also use more data sources for their Gini coefficients in order to account for any possible differences. In conclusion, no research shown significant differences in income inequality variable specification, while analysing the inequality effect on happiness. Thus we are not obliged to consider the heterogeneity of the Gini coefficients in our meta-analysis as a major problem, however we will examine it further.

Next, regarding the subjective well-being measure, which is composed of responses to the questions considering happiness or life satisfaction of the respondent, as mentioned previously in our selection criteria. Nevertheless, except for happiness and life satisfaction, also other dependent variables to study the relationship between inequality and subjective well-being exist in the literature. For example, Veenhoven (2005) mixed life expectancy with life satisfaction to get dependent variables called happy life years. Alternatively, Layte (2012) uses the WHO-Five well-being (WHO5) score, a psychometric scale composed of 5 items regarding general interest, positive mood, or vitality. Nevertheless, we did not find their measure to be relevant, but rather representing more temporary current mental well-being than the rest of well-being measures, or we found the quality of the measure unsatisfactory. Moreover, only a handful of all studies we went through during the process of data collection used other measures that happiness or life satisfaction.

Thus, the subjective well-being measure is always an ordinal, discrete variable. Nevertheless, subjective well-being measure differs in units. To obtain the subjective well-being measure, individuals are asked subjective questions about where on a scale, which can differ from 0-2 to 0-10, they are in terms of happiness or life satisfaction. For illustration, one of the examples of how the SWB data are collected is from the German Socio-Economic Panel (SOEP) asking their respondents questions on the 0-10 scale: "How satisfied are you with your life, all things considered?: 0 means 'completely dissatisfied', 10 means 'completely satisfied'." Another example is from the General Social Survey (GSS) asking Americans on the 3-points scale: "Taken all together, how would you say things are these days? Would you say that you are very happy, pretty happy, or not too happy?". Generally, these types of questions regarding life satisfaction or happiness are most frequently asked in various surveys to obtain the subjective well-being measure.

Since the subjective well-being measure is not expressed throughout our primary studies always on the same relative scale, we cannot interpret the resulting estimated coefficient of the relationship between income inequality and subjective well-being in the same way. Unfortunately, all the 53 studies researched in this meta-analysis do not use precisely the same measurement units of regression variables for the happiness-income inequality relationship. Because of this inconsistency, we need to transform the reported estimates into a standardized measure. We decided to use the standardized measure called partial correlation coefficient that nicely accounts for the difference of units for our income inequality-happiness relationship. The partial correlation coefficient (PCC) can be for our case defined as the correlation between happiness and income inequality when the impact of all other variables is partialled out.

The following formula was used to calculate the partial correlation coefficient :

$$PCC_{ij} = \frac{t_{ij}}{\sqrt{t_{ij}^2 + df_{ij}}}, \tag{3.2}$$

where:

- PCC_{ij} is the partial correlation coefficient from the regression's estimate i of the study j,
- t_{ij} represents t-statistics of the regression's estimate i of the study j,
- df denotes the degrees of freedom of this t-statistic of the regression's estimate i of the study j.

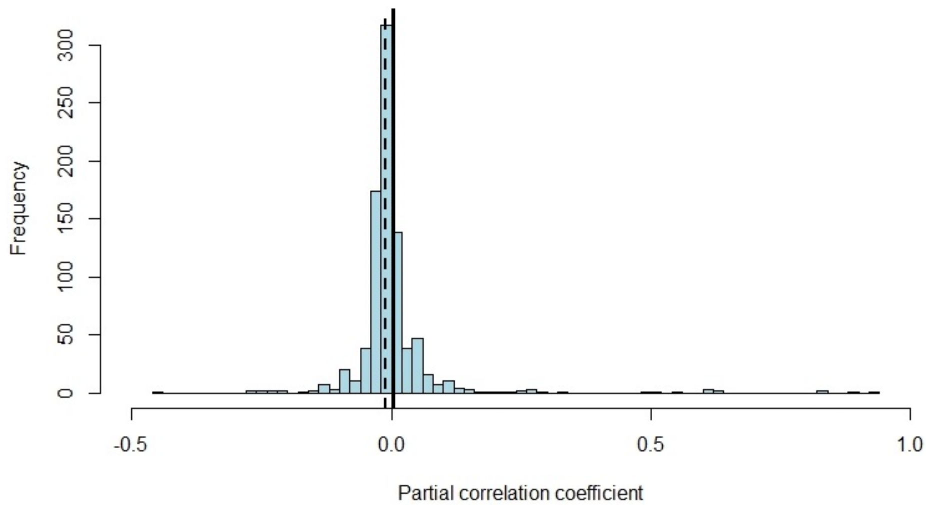
Generally, the partial correlation coefficient can take values within the range $[-1, 1]$. The closer the partial correlation coefficient is to a value of 1 in the absolute value, the larger is the effect. As presented by Doucouliagos *et al.* (2011) in his guidelines for interpreting partial correlation in economics, if $|PCC_{ij}|$ is greater than 0.33, then the relationship between the economic variables is considered to be strong. Furthermore, when $|PCC_{ij}|$ is between values 0.17 and 0.33, it is considered a medium effect and a small effect when the $|PCC_{ij}|$ is between 0.17 and 0.07.

For every PCC_{ij} we calculate the respective standard error $SE_{PCC_{ij}}$ using following formula:

$$SE_{PCC_{ij}} = \frac{PCC_{ij}}{t_{ij}} \tag{3.3}$$

After transforming our collected estimates of the happiness - income inequality relationship to partial correlation coefficients, the magnitude of the effect cannot be retained as opposed to the significance of the collected estimates, which should remain the same even after the transformation. Thus, this transformation disables the possibility to compare estimates as reported in different studies directly. The transformation technique to partial correlation coefficients is recently widely used in meta-analysis studies, researchers as Doucouliagos *et al.* (2011); Havranek *et al.* (2018); Zigraiova & Havranek (2016); Cazachevici *et al.* (2020) among many others, applied this transformation also in their studies.

Figure 3.1: Histogram of the partial correlation coefficients

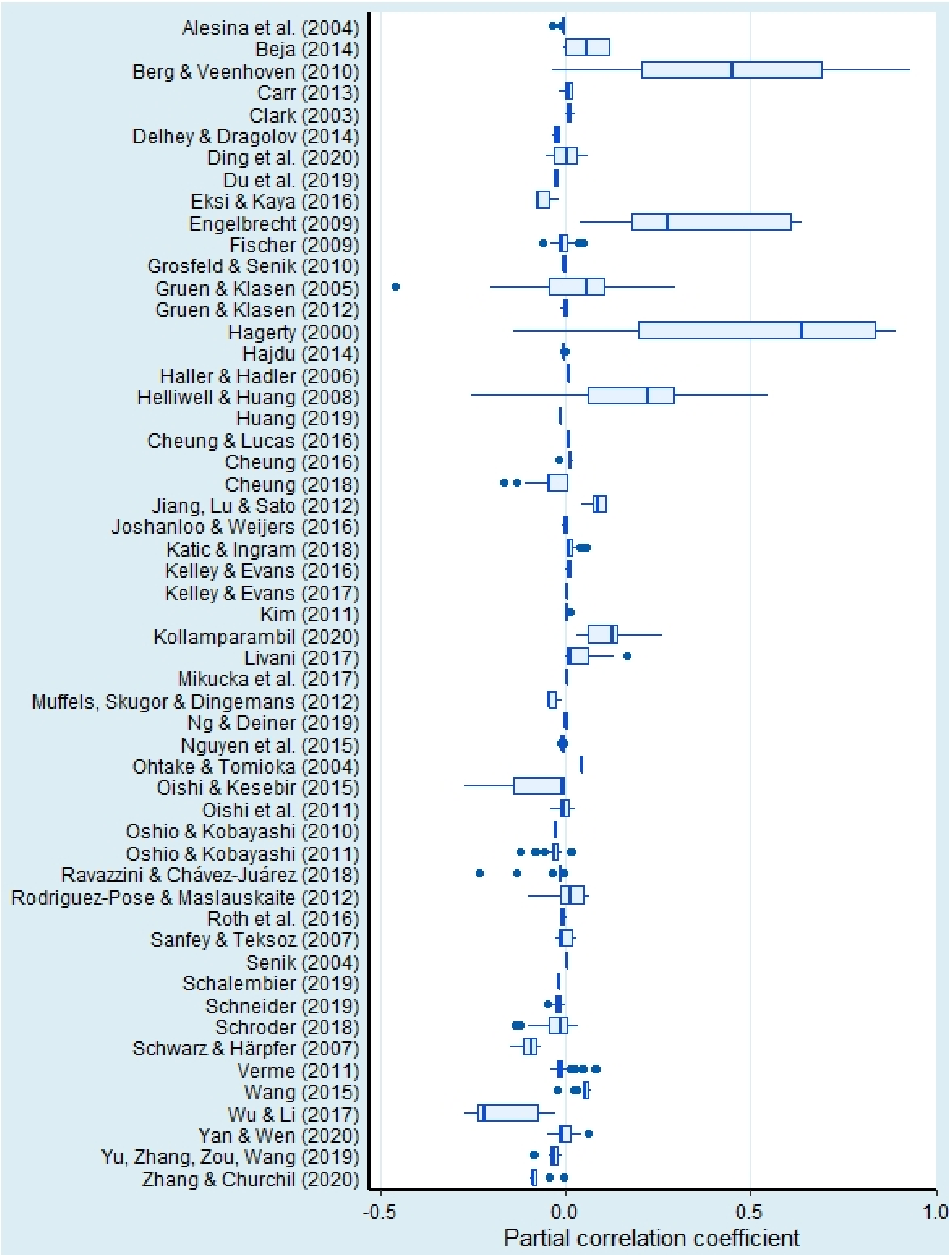


Notes: The figure shows a histogram of the partial correlation coefficients of the estimates of the income inequality effect on happiness reported by individual 53 studies. The vertical line represents the sample mean, the dashed vertical line represents the sample median.

The Figure 3.1 shows the distribution of the partial correlation coefficient (PCC) estimates of the income inequality impact on happiness presented in the 53 primary studies. The partial correlation coefficients of the effect of income inequality on happiness range from -0.498 to 0.932. Additionally, the PCC are characterized by a median of -0.010 and a mean of 0.0029. The mean is higher than the median, so the data are skewed to the right. We suppose that there exist probably a few very large partial correlation coefficients, which affect the mean more than the median, suggesting major outliers in the high end of the distribution. When we weigh the effect by the number of observations for each study, the mean is equal to -0.012. Thus, our data set probably contains some large studies with a higher number of observations with positive coefficients driving the mean up.

Next, in order to present the results of the 53 studies included in the meta-analysis, we are using the most common graphical technique called the forest plot as presented in the Figure 3.2.

Figure 3.2: Estimates distribution of income inequality effect on happiness (in PCC)



Notes: The figure depicts a box plot of the partial correlation coefficients capturing the relationship between happiness and income inequality reported in individual studies across the empirical literature.

The forest plot presented in the Figure 3.2 shows how the estimates of income inequality effect on happiness, presented in a partial correlation coefficients form, differ within as well as across all of our 53 primary studies. In detail, the boxes from the graph show the range between 25% and 75% quartile, the median depicted by a vertical line in the center of the box, and whiskers from the boxes go from each quartile to their minimum or maximum. Additionally, the outliers from each study are represented by dots. In our case, the box plot presents all the estimates, no extreme values are omitted. From the box plot, considerable cross-study, as well as within-study heterogeneity, is apparent. Further steps of our meta-analysis are likely to help us uncover the sources of this heterogeneity.

Finally, the Table 3.2 presents the summary statistics for the partial correlation coefficients for different subsets of data. For each specific subgroup of our data set, which is made based on various data characteristics, we present in the Figure 3.2 number of observations, mean estimates, and their 95% confidence interval. We separated the table into two parts since we used both the unweighted method (left-hand side) and the weighted method (right-hand side). We used the inverse of the number of estimates published per study as the weight for the weighted method so that each study has the same importance. Since most researchers use multiple model specifications, the number of estimations of the effect of income inequality on happiness varies from study to study, which causes our data set to be unbalanced. According to the guidelines by Doucouliagos *et al.* (2011), all partial correlation coefficients in the Table 3.2 imply no significant effect.

From the Table 3.2 we can see the differences across various subjective well-being (SWB) and income inequality measure specifications. It can be noted that, on average, using happiness as a measure of SWB has a positive effect compared to using life satisfaction, although it does not hold for the weighted case. Additionally, using subjective well-being measures with a 3 and 4 point measure scale is associated with positive effects compared to using other scales, similarly for the weighted case. We can also see that using the Gini coefficient based on net or gross income as income inequality measure, on average, results in a negative income inequality effect on happiness. Oppositely, using Gini based on other income groups such as expenditure or consumption, on average, is associated with a positive effect. These differences hold based on both the weighted and unweighted mean.

Table 3.2: Partial correlation coefficients for different subsets of data

	N	UnW			W		
		Mean	95%	CI	Mean	95%	CI
SWB specification							
Life satisfaction	664	-0.000	-0.008	0.006	-0.012	-0.020	-0.004
Happiness	222	0.015	0.000	0.030	-0.012	-0.03	0.003
10-11 point	576	-0.003	-0.009	0.003	-0.012	-0.018	-0.006
5, 6 and 7 point	118	-0.003	-0.014	0.009	0.018	0.007	0.029
3-4 point	159	0.018	-0.008	0.043	-0.022	-0.047	0.004
Gini specification							
Net Income Gini	486	-0.006	-0.010	0.003	-0.010	-0.014	-0.0071
Gross Income Gini	160	-0.023	-0.031	-0.014	-0.024	-0.033	-0.015
Other Gini	223	0.038	0.015	0.061	0.025	0.002	0.048
Geographical region							
Europe	275	-0.009	-0.020	0.002	-0.018	-0.030	-0.007
Asia	191	-0.010	-0.019	0.002	-0.019	-0.027	-0.010
Worldwide	328	0.014	0.002	0.026	-0.009	-0.020	0.003
Developed	318	-0.009	-0.020	0.002	-0.02	-0.032	-0.009
Emerging&Trans	207	0.008	-0.003	0.018	-0.002	-0.013	-0.008
Western	87	-0.017	-0.022	-0.013	-0.022	-0.026	-0.017
Non-Western	48	0.009	-0.019	0.035	-0.008	-0.035	0.019
Countries							
China	134	-0.000	-0.012	0.011	0.013	0.002	0.025
Japan	52	-0.032	-0.040	-0.024	-0.031	-0.039	-0.023
USA	41	0.013	-0.027	0.053	-0.001	-0.041	0.039
Germany	28	-0.041	-0.085	0.002	-0.046	-0.089	0.002
Individuals							
Poor	29	0.003	-0.021	0.028	-0.007	-0.032	0.017
Rich	31	-0.014	-0.030	0.003	-0.015	-0.032	-0.001
No. of Countries							
Only for 1 country	318	0.000	-0.012	0.012	-0.016	-0.028	-0.004
For 1-50 countries	321	-0.007	0.001	-0.001	-0.017	-0.025	-0.010
For 50+ countries	229	0.017	0.024	0.031	-0.009	-0.022	0.055
All estimates	868	0.003	-0.005	0.009	-0.012	-0.019	-0.006

Notes: The table presents unweighted and weighted mean values of the partial correlation coefficients and their 95% confidence intervals for different subsets of data. UnW = unweighted, W = weighted by the number of observations per study, N = number of observations, CI = confidence interval, SWB = subjective well-being. Europe/Asia = if estimate is for European/Asian country/ies; Worldwide = if estimate is for countries all around the world; Germany/USA/China/Japan = if estimate is for the Germany/USA/China/Japan only, Developed/Emerging & Transition = if estimate is for the developed/ emerging & transition countries; West/NonWest = if estimate is for the Western/Non-Western countries; Poor/Rich = if estimate is for poor/rich individuals from particular the country or region only, 1 country/1-50 countries/ 50+ countries= if the researchers analyzed the happiness-income inequality link based on data from 1 country/ from 1-50 countries/for more than 50

As presented in the Table 3.2, the effects also vary across countries and geographical regions. According to the mean value of the partial correlation coefficient, the income inequality effect on happiness tends to be positive for emerging & transition and non-Western countries, oppositely negative for developed and Western countries. Several studies supported our finding, such as Helliwell & Huang (2008) found out that income inequality has a negative impact on well-being in developed countries and a positive effect in developing countries, as also reported in the study of Ott (2005). Alternatively, Sanfey & Teksoz (2007) differentiated between transition and non-transition countries, and in the former they showed that income inequality has a positive effect on life satisfaction, in the latter negative. Also, Beja (2014) found out that citizens of the industrialized economies, compared to ones from the emerging economies, are likely to be more sensitive to mild levels of objective inequality.

Additionally, from the Table 3.2 we can see that income inequality has, on average, a negative impact on subjective well-being in European and Asian countries for both unweighted and weighted cases. We can also see that the mean partial correlation coefficient is positive for the USA but contrarily negative for China, Japan, and Germany. Some studies supported these findings, such as Alesina *et al.* (2004) claim that the effect of inequality on SWB appears to be less intense in the United States than in Europe. Alternatively, Delhey & Dragolov (2014) founds that income inequality lowers the degree of Europeans' subjective well-being. Also, many researchers confirmed a negative relationship between income inequality and happiness in China, such as Ding *et al.* (2020); Wang *et al.* (2015); Yu *et al.* (2019).

Next, the partial correlation coefficients of the income inequality effect on happiness is positive for the subset of poor individuals but negative for the subgroup of wealthy individuals on average. This finding is supported by, for example, Alesina *et al.* (2004), who claims that in the USA, the rich people dislike the inequality the most since they feel endangered by the mobility. Nevertheless, the results are mixed since for European countries, Alesina *et al.* (2004) observed that income inequality affects the most the lower-income group. Or Oishi *et al.* (2011), contrarily to Alesina *et al.* (2004), observed that income inequality harms the happiness of lower-income groups in the USA. Simple means of these subsets provide us with nice motivation to continue with our analysis. They can be, however, distorted by the so-called publication bias, which we will analyzed further in the next chapter.

Chapter 4

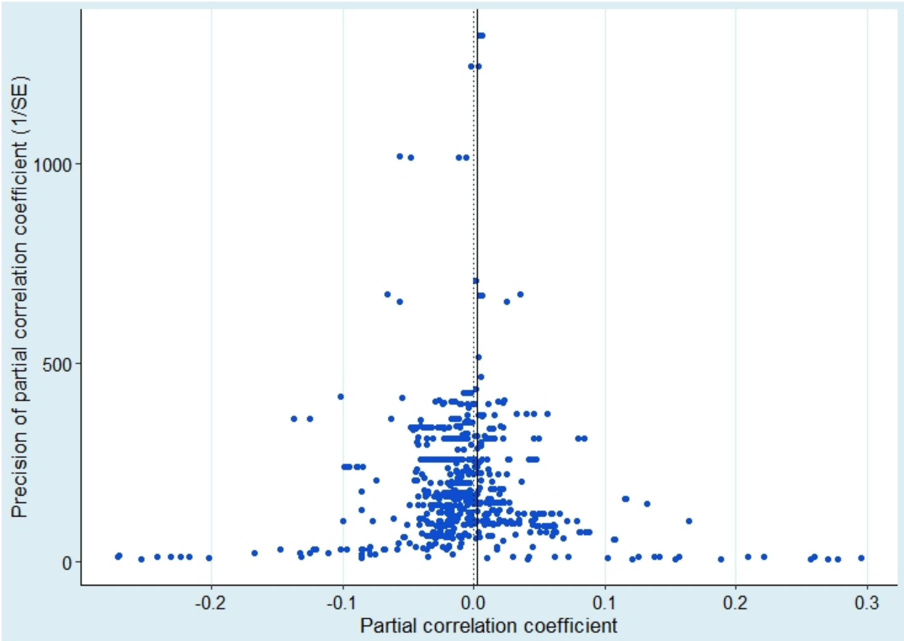
Is publication bias present?

Publication bias is the tendency of researchers or people involved in the publication process to prefer reporting statistically significant results or results supporting previous findings or underlying theory, as discussed by Stanley (2005); Doucouliagos & Stanley (2013); Gechert *et al.* (2021); Havranek & Irsova (2017). In the literature, publication bias could represent a significant issue. Since in economics, Ioannidis *et al.* (2017) shown that the mean reported coefficient could be exaggerated by two factors. Publication bias can be present in any academic field, where researchers prefer presenting specific results in their research, but publication bias does not necessarily equal cheating. Since common cause of publication bias in the literature is not presenting some results because of their lack of rationality, such as negative income elasticities of demand for any normal good, possibly caused by data issues such as small sample bias or methodological and estimation difficulties. Although, still as mentioned by Stanley (2005), some results might be intentionally selected and presented to confirm some theory, such as of previous or pronounced researcher. As well as to support some likeable hypothesis favourable for the researcher or possibly some researchers may prefer presenting only statistically significant results at standard levels. Publication bias is problematic since it can cause the true effect to be under- or over-estimated because of the over-representation of the significant results. Meta-analytical studies in many academic fields have shown the presence of publication bias even in the field of economic research. Accordingly, since no one before tested the publication bias in the empirical literature regarding the happiness-inequality relationship, it is advisable to examine it.

The simplest and most common way to begin with the publication bias analysis is to investigate the presence of publication selection using a funnel plot by Egger *et al.* (1997). The funnel plot is a graphical analyzing method of the publication bias, plotting the precision of the estimates and the size effects of the estimates. In our case, it shows estimates of the income inequality effect on happiness, expressed in partial correlation coefficient (PCC) on the horizontal axis and its precision on the vertical axis. Generally, precision measures can vary, but in our meta-analysis, we use the inverted value of standard errors. By visual investigating the funnel plot, we observe if the researchers preferred publishing only a specific direction of results. If the funnel plot resembles the symmetrical inverted funnel, then the publication bias is absent, and the observations should generally be randomly scattered around the true effect (Stanley 2005). Additionally, the highly precise observations are gathered close to the true effect. In contrast, the not as precise observations with larger standard errors are more scattered and placed at the bottom of the funnel plot. On the other hand, if the publication bias is present, the funnel plot should be skewed, so looking asymmetrically. Although there can be several causes of the funnel plot's skewness, such as heterogeneity or data quality.

The funnel plot of the partial correlation coefficients of the income inequality effect on happiness for 53 studies is depicted in the Figure 4.1. Although all 868 estimates of the happiness-income inequality relationship will be included in the further analysis, the estimates with extreme values were excluded for better visual inspection of the funnel plot. Based on the Figure 4.1, we could say that the funnel plot of the happiness-inequality relationship rather resembles a funnel and suggest almost zero true effects. Although from the funnel plot in the Figure 4.1 can be seen that there are more observations on the left part of the plot, suggesting that negative estimates are preferred to be reported by researchers. It also supports the prevailing theory view of the negative relationship between happiness and income inequality, suggesting that higher inequality is likely to make people less happy. Thus, even though most estimates are scattered around zero, the funnel plot is not perfectly symmetrical. Although, our funnel plot is not hollow and even primary studies report some estimates with very small precision at the bottom of the plot. Additionally, the slight asymmetry of the funnel plot with a denser left-hand side may be caused by heterogeneity as well. Overall, the funnel plot suggests some publication bias, but more rigorous tests need to be applied since the graphical analysis of the funnel plot could be subjective.

Figure 4.1: Funnel plots suggest some publication bias



Notes: The horizontal axis depicts the income inequality effect on SWB expressed in partial coefficient correlations, not winsorized on any distributions' side, and the vertical axis depicts the precision expressed by the inverted standard errors of partial coefficient correlations. The mean effect is represented by the solid vertical line, and zero mean coefficient of the effect is represented by the dashed vertical line.

Funnel asymmetry test and precision effect test also called the FAT-PET, address the problem of detecting publication bias more rigorously by using the following linear approximation of the relationship between the effects from primary studies in partial correlation coefficients and their standard errors:

$$PCC_{ij} = \beta_0 + \beta_1 \; SE(PCC_{ij}) + \epsilon_{ij}, \tag{4.1}$$

where:

- PCC_{ij} is the i-th effect estimate of partial correlation coefficient from the j-th study,
- β_0 represents the mean PCC (the "true" underlying effect) corrected for the publication bias,
- β_1 represents publication bias,
- $SE(PCC_{ij})$ denotes its standard error of PCC,
- ϵ_{ij} is the error term of the of the i-th estimate in the j-th study.

The Funnel Asymmetry Test (FAT), which uses Equation 5.1 as a linear approximation, gets its name from rotating the funnel plot's axes and inverting the values on the new horizontal axis so that standard errors, rather than precision, are shown. The Funnel Asymmetry Test tests the null hypothesis $H_0 : \beta_1 = 0$ against its alternative hypothesis $H_1 : \beta_1 \neq 0$, so whether the publication bias is present or not. Then, the Precision Effect Test (PET) is applied with the same mathematical equation as FAT, it tests the null hypothesis of $H_0 : \beta_0 = 0$, against its alternative hypothesis $H_1 : \beta_0 \neq 0$, so examining the mean value of the estimates of PCC after correction for publication bias, estimating the genuineness of the effect. In case of no publication bias ($\beta_1 = 0$), the observed partial correlation coefficients should be independent of their standard error and scattered randomly around the true value β_0. Thus as mentioned by Stanley (2005), the coefficient β_1 should be statistically not different from zero. Oppositely, if publication bias is present and significant ($\beta_1 \neq 0$), it follows from the regression equation that the correlation between the partial correlation coefficient and their standard error should be observed. The reasons for that could be that the researchers tend to remove some estimates of the partial correlation coefficients or could also account for large standard errors with large estimates of the partial correlation coefficients. Therefore, in the event of the null hypothesis of FAT and PET being rejected, publication bias and the "true" underlying effect exist. The classification by Doucouliagos & Stanley (2013) states that "If FAT is statistically significant and if $1 \leq |\beta_1| \leq 2$, then there is 'substantial' selectivity", and if $|\beta_1| > 2$ then the selectivity is 'severe', additionally that if $|\beta_1| < 1$ or is statistically insignificant then the selectivity is 'little to modest'.

Linear tests of funnel asymmetry presented in the Table 4.1 try to correct for heteroskedasticity by explaining the variation across the studies in the partial correlations coefficients. In order to account for probable within-study correlation of reported results, all specifications from the Table 4.1 are estimated with standard errors clustered at the study level. Also, all methods are using the data-set of the meta-analysis with the partial correlation coefficients with their standard errors winsorized at 1% level on both distributions' side. We have divided the Table 4.1 into Panel A, representing unweighted techniques, and Panel B, representing weighted techniques. The first specification in the Table 4.1 (Panel A: unweighted, OLS column) represents the results of the funnel asymmetry test (FAT), followed by other specifications in other columns serving as robust checks.

Table 4.1: Linear tests of funnel asymmetry suggest publication bias in unweighted specifications

	OLS	*FE*	*BE*
Panel A: unweighted			
Standard error	1.526 ***	0.626 ***	1.153 ***
(publication bias)	(0.334)	(0.060)	(0.129)
Constant	-0.018***	-0.011***	-0.014***
(effect beyond bias)	(0.003)	(0.000)	(0.002)
		Precision	*Study*
Panel B: weighted			
Standard error		0.626	0.160
(publication bias)		(0.492)	(0.302)
Constant		-0.013***	-0.011***
(effect beyond bias)		(0.002)	(0.003)
Observations	868	868	868
Studies	53	53	53

Notes: The table presents the results of the regression: $PCC_{ij} = \beta_0 + \beta_1\ SE(PCC_{ij}) + \epsilon_{ij}$ with PCC as a dependent variable. The standard errors of the regression parameters are clustered at study level and shown in parentheses. OLS = ordinary least squares, FE = study-level fixed effects, BE = study-level between effects, Precision = weighted by the inverse of the reported estimate's standard error, Study = weighted by the number of estimates reported per study, Standard errors are reported in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. We also performed these test for sub-sample of 576 comparable estimations of the income inequality effect on happiness, before its transformation to PCC, and results were very similar.

As can be seen from the Table 4.1, our first method to estimate the partial correlation coefficient based on its standard error was simple OLS regression. This specification results in positive β_1 significant at 1% level, which based on classification by Doucouliagos & Stanley (2013) represents substantial publication bias. Additionally, it results in negative but very close to zero β_0 significant also at 1% level, representing the mean ("true") PCC corrected for publication bias. The key assumption of this method is that the error terms u_{ij} should be uncorrelated across studies, but in various clusters separately (within the same study) can be correlated. Nevertheless, the error term u_{ij} is likely to vary with studies, so its variance together will not be constant because of different sample size and modelling specifications of the studies, which contradicts the key assumption of regression analysis about the error term's family. Therefore, the standard errors, confidence intervals, and other statistics can be misleading.

Since our data set for meta-analysis is, however, rather unbalanced and heterogeneous because of the selection of different variables and possibly different methodological approaches to investigating the happiness-income inequality relationship, we additionally used other five linear methods.

Thus, second set of coefficients comes from the fixed-effects estimation technique ("FE"). To our basic model (Equation 4.1), we added term representing characteristics that can vary across various studies but not within the study. This new vector of study specific affects is expected to be independent of standard error and the error term and normally distributed. The fixed-effect method control for any quality characteristics specific to individual studies, so it is better at detecting unobserved study-specific heterogeneity. Although among the disadvantages of the fixed-effect method belongs possibly losing some information and only exploiting the within-study variation. As the third and final unweighted linear estimation method presented in Panel A of the Table 4.1, we applied is the between-effects estimation ("BE"), which uses between-study variance instead of within-study variance and serves as a robust check. Compared to fixed-effect, the study weights are more balanced while using the between-effects model since less weighs are assigned to larger studies, and vice-versa. Additionally, greater efficiency can be achieved using between-effects, resulting in smaller standard errors of coefficients and higher statistical power for detecting the effects. The results using both the fixed-effects and between-effects methods are similar to the OLS method regarding the significance as well as magnitude of both indicators, just the β_1 coefficient representing the publication bias is not as large.

Next method applied, presented in the Table 4.1 in Panel B: weighted, denoted as "Precision" is the weighted least squares regression weighted by the precision, which is an inverse of the standard error. This method is applied in order to obtain efficient estimates with corrected standard errors. The principle of weighting all observations lies in assigning larger weights to more precise estimates, and oppositely assigning smaller weights to less precise estimates and correcting the models for heteroscedasticity. As the final fifth linear weighted method presented in the Table 4.1 Panel B, denoted as "Study", we used regression weighted by the inverse of the number of estimates reported per a study in order to diminish the effect of studies reporting many estimates and to treat the large and small studies equally. For both regressions, the estimated effect beyond bias remained both statistically significant at 1% level, negative and close to zero, but the coefficient representing the publication bias changed to being insignificant and less large, representing little to modest selection based on Doucouliagos & Stanley (2013).

The Table 4.2 represents the results using methods for detecting publication bias without the necessity of any assumptions regarding the relationship between the effect and its standard error:

Table 4.2: Tests for detecting publication bias with relaxed exogeneity assumption

	IV	*p-uniform**	*p-uniform*
Standard error	1.922***	Not	Not
(publication bias)	(0.541)	sign.	sign.
Constant	-0.023***	-0.002	-0.015***
(effect beyond bias)	(0.005)	(0.008)	(0.004)
Observations	868	868	868
Studies	53	53	53

Notes: The standard errors of the regression parameters are clustered at study level and shown in parentheses. IV = panel data instrumental variables regression with the inverse of the square root of the number of estimates reported per study used as an instrument, p-uniform*= test for publication bias developed by van Aert & van Assen (2020) based on the distribution of p-values, p-uniform = older test for publication bias developed by van Assen *et al.* (2015) based on the distribution of p-values. "Not sign." = meaning that the publication bias is statistically insignificant. Standard errors are reported in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

The first estimation method with relaxed exogeneity assumption, we decided to apply in the Table 4.2 is the instrumental variable (IV) estimation method. We prevent the coefficient whose standard errors are correlated with error terms or are estimate themselves. We selected the instrumental variable to be equal to the inverse of the square root of the number of estimates reported per study, since it should be highly correlated with standard error but uncorrelated with error terms. The results of the instrumental variable approach provided the highest publication bias coefficient (almost equal to two) and still significant at 1% level. According to classification by Doucouliagos & Stanley (2013), it represents substantial almost severe publication bias. The estimate of effect beyond bias is also similarly statistically significant, negative and close to zero.

Additionally, as another tool for controlling the heterogeneity of the design of the primary studies, and possibly also for some unobserved effects correlated with both partial correlation coefficients and their standard errors, we decided to perform is p-uniform* by van Aert & van Assen (2020). While using the p-uniform*, we can also relax the exogeneity assumption, so we do not need the assumption of zero correlation between partial correlation coefficients and their standard errors in the absence of publication bias. This approach by van Aert & van Assen (2020) is a relatively new technique, firstly used in psychology, but also very useful for testing and correcting for publication bias. P-uniform* is based on the principle of uniformly distributed p-values at the "true" underlying effect. This technique tries to find a coefficient with approximately uniformly distributed p-values, by comparing the distributions of recalculated reported p-values for various possible values of the underlying effect. Thus, the publication bias is tested for by evaluating whether p-values are uniformly distributed at the mean effect collected from the literature. Specification p-uniform* by van Aert & van Assen (2020) is a newer and revised technique of p-uniform developed by van Assen *et al.* (2015). The benefits of the improved p-uniform* technique are eliminating overestimation because of heterogeneity, bigger efficiency compared to the p-uniform's estimator, and finally, the possibility of estimating and testing the heterogeneity extent.

Generally, our results suggest that our primary literature obtains several studies with high number of observations, which if each estimate have the same weight causes publication bias. Nevertheless, if we use weighting of the observations based on the number of observations, so we give equal weight to each study, then the publication bias decreases. As can be seen from results of weighted estimation techniques in the Panel B of the Table 4.1, and also above in the Table 4.2 from the p-uniform* and p-uniform results, which create equal weight for each study by using median, not weighted average. The mixed results for the Table 4.2 are probably caused by comparing the weighted estimation techniques (p-uniform*/p-uniform) to linear unweighted estimation technique (IV), which significantly supports the presence of publication bias. Similarly, to other unweighted linear specifications as presented in the Table 4.1, Panel A. Although still, the estimates of effect beyond bias are statistically significant, negative and close to zero, as in previous cases.

In our meta-analysis, we apply next to linear techniques also non-linear techniques to estimate the "true" underlying effect since the relationship between the size of publication bias and its standard error does not have to be linear. In the table Table 4.3, the results of recently developed, non-linear tests of funnel asymmetry techniques concerning the publication bias are presented. In particular, we applied five different methods: the Weighted average of adequately powered estimates by Ioannidis *et al.* (2017), the Selection model by Andrews & Kasy (2019), the Stem-based method by Furukawa (2019), the Top 10 method by Stanley *et al.* (2010), and the Endogenous kinked model by Bom & Rachinger (2019), all five non-linear tests presenting similar results.

Table 4.3: Non-linear tests for detecting publication bias

	WAAP *Ioannidis* et al. *(2017)*	*Selection model* *Andrews & Kasy (2019)*
Effect beyond bias	-0.010*** (0.002)	-0.008*** (0.001)
	Stem-based method *Furukawa (2019)*	*Top 10 method* *Stanley* et al. *(2010)*
Effect beyond bias	-0.010 (0.013)	-0.008* (0.003)
	Kinked model *Bom & Rachinger (2019)*	
Effect beyond bias	-0.010*** (0.001)	
Observations	868	868
Studies	53	53

Notes: Standard errors are reported in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

The first nonlinear method we decided to use was created by Ioannidis *et al.* (2017) and is called the weighted average of the adequately powered (WAAP). This technique by Ioannidis *et al.* (2017) is based on estimates weighted by their average with weights proportional to the estimate's precision and focuses just on estimates with adequate statistical power. The correction proposed by this method aims at estimates with statistical power above 80%. Using this technique by Ioannidis *et al.* (2017), we obtain a mean partial correlation coefficient of the income inequality effect on happiness equal to -0.01, which is in line with the estimates of linear techniques, suggesting a negative relationship between income inequality and subjective well-being although close to zero. The second nonlinear method is by Andrews & Kasy (2019), and it is commonly called the Selection model. The Selection model is a non-parametric approach based on confidence sets and estimators corrected for publication bias. This correction and identification of the bias need to previously know the conditional probability of publication selection given their p-values distribution. Thus, this method is based on the fact that some studies, such as those with statistically significant results, are more likely to be published. The coefficient obtained by the selection model technique is -0.008, which is slightly higher than the previous result of the WAAP. Graphs and table from this model by Andrews & Kasy (2019) is in Appendix A.

The third nonlinear estimation technique used is called the Stem-based method by Furukawa (2019). The Stem-based method is also a non-parametric method that robustly selects the number of the most precise studies (the stem of the funnel plot) based on an algorithm minimizing mean standard error. Its advantage is that it is robust to various assumptions regarding the distribution of "true" effects as well as the functional form of publication bias. It is generally considered a more conservative method because of wide confidence intervals. This approach by Furukawa (2019) is similar to one by Stanley *et al.* (2010) since both methods are using just some proportion of estimations selected based on their precision level. We also performed this method by Stanley *et al.* (2010), which is called the Top 10. Stanley *et al.* (2010) advises using just 10% of the most precise estimates. Contrarily to Furukawa (2019), who does not have a determined concrete number or portion of the most precise results in advance, but calculates it optimally every time based on specific data set. Again similarly, the resulted coefficients from both the Stem-based method and Top 10 method are approximately -0.01, although they are not statistically significant compared to prior results. The final nonlinear estimation technique we decided to use is the Endogenous kinked model by Bom & Rachinger (2019). This technique is similar to the stem-based method since it is also based on estimating Monte Carlo simulations. Bom & Rachinger (2019) in his technique accounts for when estimates must achieve some precision level to be reported and estimates this level. The kinked model assumes that highly precise estimates are not biased and use two linear segments to fit the model and the place where this segment joins calls kink. Again, the coefficient obtained by the kink model is -0.01 with a 1% significance level.

Generally, we can conclude two important findings. Firstly, the publication bias in the literature regarding the relationship between happiness and income inequality is present based on unweighted methods. Since the null hypothesis $H_0 : \beta_1 = 0$ of the Funnel Asymmetry Tests (FAT) can be rejected, based on findings presented in Table 4.1 and Table 4.2. In four unweighted linear specifications (OLS, FE, BE in the Table 4.1 and IV in the Table 4.2) out of all six, β_1 is statistically significant at a 1% level, in three cases it is larger than 1, and in one case is larger that 0.5. Thus, according to classification by Doucouliagos & Stanley (2013) as mentioned previously, a substantial selectivity is present in unweighted specifications. Nevertheless, the weighted estimation methods do not find the presence of publication statistically significant, as can be seen from the results of Panel B of Table 4.1, where precision and study-related weights are applied, or from the results of p-uniform*/p-uniform in the Table 4.2. Thus, several larger studies with a higher number of observations in our primary literature cause publication bias, but when we give equal weight to each study, the presence of publication bias is not significant.

Secondly, we cannot reject the null hypothesis $H_0 : \beta_0 = 0$ of Precision Effect Test (PET), since the results of effect beyond bias suggests that the mean partial correlation coefficient of the happiness-income inequality effect corrected for the publication bias is rather small negative number and close to zero and statistically significant at a 1% level. As confirmed by all linear estimation methods from Table 4.1, two out of three estimation methods without the exogeneity assumption from Table 4.2, and two out of four non-linear methods from Table 4.3. All of them suggest that the robust estimate of the mean partial correlation coefficient representing the happiness-income inequality relationship after correcting the literature for publication bias is approximately -0.01 with 1% level significance, in comparison with the mean estimate prior to the correction for publication bias which is equal to 0.003, signifying that the effect corrected for the publication bias is very small. Additionally, the unweighted sample mean beyond publication bias shows an effect closer to the simple weighted mean. To conclude, the unweighted sample shows substantial publication bias. Still, some correlations between the effects and their standard errors can be because of data and method heterogeneity, which we will investigate in the next chapter.

Chapter 5

Why the effects vary?

Aside from the publication bias, the remaining sources of heterogeneity of data caused by being sourced from 53 different studies must also be accounted for. Since as Ngamaba *et al.* (2018) conclude, the ambiguous results in the respective literature can be explained by the fact that several factors influence the magnitude and direction of the happiness-inequality link. They emphasize the importance of factors and the calls for their future examination. As mentioned by Zhang & Churchill (2020), for example, trust in people is one of the topics that has gotten much attention in the related literature. Nevertheless, many factors could generally explain the variation in estimates, not only control variables from the study model but also variable specifications, data characteristics, estimation methods, and publication characteristics of the study. Thus, the number of possible explanatory variables may be very large.

Significant heterogeneity in our data set through studies included in our meta-analysis could be seen from Figure 3.2 and Table 3.2, demonstrating the heterogeneity does not have to come only from publication bias. This variation in reported estimates of the happiness-income inequality link across studies should be investigated further by regressing the partial correlation coefficients of the estimates on explanatory variables. To analyze the systematic patterns in the heterogeneity of the happiness-income inequality effect, we are going to use the following multivariate meta-regression:

$$PCC_{ij} = PCC_0 + \beta_j * \sum_j X_{ij} + u_{ij}, \tag{5.1}$$

where:

- PCC_{ij} represents the partial correlation coefficient of the happiness-income inequality effect estimate,
- PCC_0 represents the constant term
- β_j identifies the vector of the coefficients,
- X_{ij} denotes the explanatory variables capturing study characteristics, including the publication bias
- u_{ij} is the error term.

Equation 5.1. is an expansion of Equation 4.1. Thus, we have extended the basic model from publication bias investigation by including study characteristics in order to address variability in the literature and investigate what drives it. We collected any possible additional characteristics, as shown in the Table 5.1, that are likely to explain the heterogeneity among the estimates when going through all 53 studies. Since, as seen in the previous chapters, the impact of income inequality on happiness differs significantly across studies. The explanation may be that the magnitude of the happiness-income inequality effect is determined by a number of study characteristics, resulting in heterogeneity of results.

The Table 5.1 describes all of the 78 explanatory variables we collected from our primary studies on the happiness-income inequality literature presented in Table 3.1. The table shows their simple means, standard deviations, and means weighted by the inverse of the number of estimates reported per study. For a better overview of the variables, we have grouped all of the 78 study characteristics into the following categories: SWB specifications, Income inequality specifications, Data characteristics, Structural variation, Estimation characteristics, Macroeconomic effects, Microeconomic effects, and Publication characteristics. We later comment on further how our primary studies vary within these groups of variables, to understand the importance of each variable to help explain the heterogeneity among the estimated income inequality effects on subjective well-being.

Table 5.1: Description and summary statistics of regression variables

Variable	Description	Mean	SD	WM
Partial correlation coef.	Partial correlation coefficient derived from the estimate of the SWB - income inequality relationship	0.00	0.10	0.02
Standard Error	The standard error of the happiness-income inequality effect estimate	0.01	0.02	0.02
Subjective well-being (SWB) specifications				
Happiness	=1 if happiness is used as a measure of SWB	0.26	0.44	0.32
Life satisfaction	=1 if life satisfaction is used as a measure of SWB	0.76	0.42	0.74
SWB: 10-11 point scale	=1 if 10 or 11 point scale is used for responding to the question about SWB	0.66	0.47	0.55
SWB: 5-7 point scale	=1 if 5,6 or 7 point scale is used for responding to the question about SWB	0.14	0.34	0.21
SWB: 3-4 point scale	=1 if 3 or 4 point scale is used for responding to the question about SWB	0.18	0.39	0.20
SWB: WVS data	=1 if the World Values Survey is used as source of SWB data	0.36	0.48	0.28
SWB: EVS data	=1 if the European Values Survey is used as source of SWB data	0.39	0.49	0.20
SWB: ESS data	=1 if the European Social Survey is used as source of SWB data	0.05	0.21	0.05
SWB & Gini: CGSS data	=1 if the Chinese General Social Survey is used as source of both SWB and Gini data	0.08	0.27	0.06
Income inequality specifications				
Gini: Net Income	=1 if the Gini index is calculated based on net income	0.56	0.50	0.4
Gini: Gross Income	=1 if the Gini index is calculated based on gross income	0.18	0.39	0.12
Gini: WB data	=1 if the World Bank database is used as data source for the Gini index	0.10	0.30	0.24
Gini: SWIID data	=1 if the Standardized World Income Inequality Database is used as data source for the Gini index	0.11	0.32	0.1
Gini: WIID data	=1 if the World Income Inequality Database is used as data source for the Gini index	0.11	0.31	0.07
Gini: DS data	=1 if the Deininger and Squire database is used as data source for the Gini index	0.03	0.18	0.07
Gini: OECD data	=1 if the OECD database is used as data source for Gini coefficient	0.18	0.39	0.03

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Table 5.1: Description and summary statistics of regression variables (continued)

Variable	Description	Mean	SD	WM
Gini: Eurostat data	=1 if the Eurostat database is used as data source for the Gini index	0.07	0.25	0.06
Data characteristics				
Data midpoint	Logarithm of the mean year of time period used for estimation minus the earliest mean year	1.31	0.21	1.3
Data length	Logarithm of the number of years used for estimation	0.74	0.56	0.75
Data size	Logarithm of the number of observations used for estimation	4.33	0.84	4.12
No of countries	Logarithm of the number of countries on which the study's data are based on	0.95	0.77	0.8
Macro level	=1 if the number of observations is country- or regional-level based	0.08	0.27	0.19
Micro level	=1 if the number of observations is individual-level based	0.92	0.27	0.83
1 country	=1 if the researchers analyzed the happiness-income inequality link based on data from 1 country	0.37	0.48	0.1
1-50 countries	=1 if the number of countries on which the study's data are based is between 1 and 50	0.38	0.49	0.25
50+ countries	=1 if the number of countries on which the study's data are based higher than 50	0.26	0.44	0.17
Structural variation				
Europe	= 1 if estimate is for European country/ies	0.32	0.47	0.24
Asia	= 1 if estimate is for Asian country/ies	0.22	0.41	0.27
Worldwide	= 1 if estimate is for countries all around the world	0.38	0.49	0.35
Germany	= 1 if estimate is for Germany only	0.03	0.18	0.05
United States	= 1 if estimate is for the United States only	0.05	0.21	0.07
China	= 1 if estimate is for China only	0.15	0.36	0.19
Japan	= 1 if estimate is for Japan only	0.06	0.24	0.06
Developed	= 1 if estimate is for the developed country/ies	0.37	0.48	0.34
Emerging & Transition	= 1 if estimate is for the emerging or transition country/ies	0.24	0.43	0.33
Western	= 1 if estimate is for the group of Western countries	0.10	0.30	0.03
Non-Western	= 1 if estimate is for the group of Non-Western countries	0.06	0.23	0.05
Poor	=1 if estimate is for poor individuals only	0.03	0.18	0.03

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Table 5.1: Description and summary statistics of regression variables (continued)

Variable	Description	Mean	SD	WM
Rich	=1 if estimate is for rich individuals only	0.04	0.19	0.04
Estimation characteristics				
OLS	=1 if ordinary least squares is used as the estimation method	0.24	0.42	0.22
Logit	=1 if ordered logit is used as the estimation method	0.32	0.47	0.13
Probit	=1 if ordered probit is used as the estimation method	0.08	0.27	0.13
FE	=1 if fixed effects is used as the estimation method	0.22	0.42	0.24
RE	=1 if random effects is used as the estimation method	0.05	0.22	0.08
Multilevel	=1 if multilevel linear estimation model is used	0.31	0.46	0.38
Country level	=1 if the analysis in a primary study is at country level	0.69	0.46	0.58
Regional level	=1 if the analysis in a primary study is at regional level	0.31	0.46	0.42
Area dummy	=1 if country or regional dummies are accounted for	0.73	0.45	0.54
Year dummy	=1 if year dummy is accounted for	0.64	0.48	0.47
Macroeconomic effects				
GDP	=1 if GDP is controlled for in the regression specification	0.54	0.50	0.51
Income macro	=1 if income of country or region is controlled for in the regression specification	0.08	0.27	0.16
Inflation	=1 if inflation is controlled for in the regression specification	0.12	0.32	0.13
Unemployment	=1 if unemployment is controlled for in the regression specification	0.18	0.38	0.23
Government quality	=1 if governmental quality is controlled for in the regression specification	0.07	0.26	0.09
Inequality reduction	=1 if inequality reduction is controlled for in the regression specification	0.05	0.21	0.06
Freedom	=1 if freedom is controlled for in the regression specification	0.03	0.18	0.07
Microeconomic effects				
Age	=1 if age is controlled for in the regression specification	0.77	0.42	0.74
Gender	=1 if gender is controlled for in the regression specification	0.76	0.43	0.73

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Table 5.1: Description and summary statistics of regression variables (continued)

Variable	Description	Mean	SD	WM
Race	=1 if race is controlled for in the regression specification	0.10	0.30	0.11
Education	=1 if education is controlled for in the regression specification	0.73	0.44	0.63
Employment	=1 if employment status is controlled for in the regression specification	0.60	0.49	0.44
Residetial	=1 if residential status is controlled for in the regression specification	0.21	0.41	0.28
Marital	=1 if marital status is controlled for in the regression specification	0.65	0.48	0.63
Income micro	=1 if individual or household income is controlled for in the regression specification	0.79	0.41	0.73
Relative income	=1 if relative income is controlled for in the regression specification	0.21	0.41	0.11
Religion	=1 if religion is controlled for in the regression specification	0.29	0.45	0.23
No of children	=1 if number of children is controlled for in the regression specification	0.22	0.42	0.21
Household size	=1 if household size is controlled for in the regression specification	0.16	0.37	0.12
Health	=1 if health is controlled for in the regression specification	0.24	0.42	0.32
Trust	=1 if trust in people is controlled for in the regression specification	0.33	0.47	0.23
Political	=1 if political status is controlled for in the regression specification (i.e. communist party member)	0.28	0.45	0.13
Mobility	=1 if perceived social mobility is controlled for in the regression specification	0.04	0.21	0.04
Hukou	=1 if Hukou is controlled for in the regression specification	0.13	0.33	0.1
Publication characteristics				
Publication year	Logarithm of the year the study was published minus the earliest year	1.13	0.20	1.12
Impact factor	The recursive discounted impact factor from RePEc	0.91	0.48	0.15
Citation	Logarithm of the number of study citations in Google Scholar per year since the study was published	0.16	0.23	0.89

Notes: The tables shows the regression variables, their description and summary statistics. Mean = arithmetic mean, SD = standard deviation, WM = mean weighted by the inverse of the number of estimates reported per study.

Subjective well-being specifications

As discussed in the previous chapters, there are two ways to categorize the subjective well-being measure in the literature, either as happiness or life satisfaction measure. Since they are very similar, as reported by several researchers (Frey *et al.* 2018; Ferrer-i Carbonell & Ramos 2014; Tella *et al.* 2003), most researchers throughout fields use terms subjective well-being, happiness, and life satisfaction interchangeably. In our thesis, we have decided to test the correctness of their hypothesis by dividing which estimates used happiness and which life satisfaction measure. From the Table 3.2, we can see that the mean reported estimates based on the happiness measure might vary from the estimates using the life satisfaction measure. We have decided to include the dummy variable happiness to determine if the difference still holds after controlling for other characteristics of our data.

As mentioned by Schneider (2016), generally the majority of the research on the relationship between inequality and well-being uses life satisfaction measure as the dependent variable. Our data-set confirms this statement since approximately one-third of the estimates use happiness measure as a dependent variable, and more than two-thirds of estimates use life satisfaction measure. As the reference category, we use the life satisfaction-based estimations or estimations that use both. Additionally, we decided to control for how many points the scale used for the response on the subjective-well-being question have since certain heterogeneity can remain untreated despite the transformation of the estimates to partial correlation coefficients. Even though we have not come across any review or study that specifically addresses this form of heterogeneity, we have decided to control for it because it may also represent a source of heterogeneity. As previously mentioned and as can be seen from

Table 3.2, the majority of all estimates (approximately two-thirds) used the subjective well-being measure based on a scale of ten or eleven points. Furthermore, approximately 18% of estimates used subjective well-being measures based on a scale with three or four points, and 13% with five, six, or seven points. The reference category represents the estimates based on subjective well-being measure with other scales than those mentioned above.

Data about happiness and life satisfaction can be obtained from various sources. Researchers are limited in their choice of SWB indicators, depending on the source of data. For worldwide studies, the most frequently used databases are the World Value Survey (WVS) and the World Database of Happiness (WDoH), both with a 10-point scale. For the European area, the Eurobarometer and the European Value Study (EVS) with 10-point scales are most often used. Furthermore, for the Latin American area, Latinobarometro with a 4-point scale is often used. On the other hand, for making regional-level analyses, researchers use: the American General Social Survey (GSS) with 3-points scale, the German Socio-Economic Panel Study (SEOP) with 11-point scale; the British Household Panel Study (BHPS) with 7-point scale; the Russian Longitudinal Monitoring Survey (RLMS) with 6-point scale and others.

Specifically, Alesina *et al.* (2004) in their study analyzes the income inequality effect on subjective well-being using life satisfaction data from the Eurobarometer with a 10-point scale for Europe, and the happiness data from the GSS with 10-point for the United States. Alternatively, Berg & Veenhoven (2010) study life satisfaction using WDoH with a 10-point scale. Or, Rözer & Kraaykamp (2013) use the WVS data and creates a new dependent variable using the mean of both happiness and life satisfaction, recording the 4-point scale of happiness into a 10-point scale in order to be comparable with the measure of life satisfaction. Next, Clark (2003) examines the relationship between income inequality and life satisfaction using BHPS with a 7-point scale.

The World Values Survey (WVS) is the most widely used worldwide subjective well-being database in our meta-analysis, accounting for 36% of all estimates. The World Values Survey is a survey of the 120 countries holding every five years assessing the various social, political, and economic development of countries over time. The World Database of Happiness (WDoH) is the second most used worldwide database, however, it is not used often enough in our data collection to be accounted for. Next, the most used European database of happiness is the European Values Survey (EVS) with 38% of estimates, followed by the European Social Survey (ESS) with 8% of estimates. The European Values Survey provides data from 1981 to 2017 with increasing quality and repeatedly interviews representative samples of each country's resident adult population. The European Social Survey is the second most frequent data source for European countries and has been providing data on European society's perceptions, values, and activities for 30 countries since 2002.

The data sources of subjective well-being measures used by the 53 primary studies on country-level are less heterogeneous than of income inequality measures. Nonetheless, the data sources for income inequality and subjective well-being at the regional level are almost the same. For regional-level analysis, researchers used data from national databases for China (CGSS, CFPS, CMDS, CHIP, CLDS), Australia (HILDA), Germany (SOEP), the United Kingdom (BHPS), Russia (RLMS), the United States (GSS, BRFSS), Japan (CSLCPHW & JGSS), or South Africa (National Income Dynamics data) and others. Unfortunately, these datasets are not frequent enough in our meta-analysis to be controlled for in our meta-analysis regression, except for data sets CGSS and

CSLCPHW & JGSS with frequency 8% and 5% of all estimates. Since the data set CSLCPHW & JGSS are the only ones used for analyzing Japan, its inclusion as a control variable is pointless. Nevertheless, we have decided to control for the CGSS (Chinese General Social Survey) data source since it is one of five used data sources for China.

Income inequality specifications

Since we also try to address the potential heterogeneity in the Gini coefficients, we added control variables indicating which income group the Gini coefficient is based on. More than half of the estimates use the Gini coefficient based on net income as the income inequality measure, such as Cheung & Lucas (2016); Hajdu & Hajdu (2014); Verme (2011). Although the term "net income" has been given various names in different studies, such as "post-government income" or "disposable income," the meaning remains the same, it is simply income after taxes and government transfers. Approximately one-fifth of the estimates use the Gini coefficients based on gross income, such as Oshio & Kobayashi (2010); Fischer (2009) or Gruen *et al.* (2005). Similarly, also the term "gross income" is referred to in a number of ways, such as "market income" or "pre-government income," but it can be simply defined as income before taxes and transfers from the government. The reference group is the estimates using the Gini coefficient based on unspecified income, expenditures, or possibly consumption.

Regarding Gini coefficients and their sources, researchers most often choose the general country-level databases with already computed Gini coefficients, including countries around the world. Nevertheless, it might be harder to obtain the regional-level Gini coefficient. Thus, few of our primary studies calculate their own Gini coefficients based on income data. For example, Clark (2003) calculated the Gini from within their own surveys or Carr (2013) based on gross income data from the General Social Survey (GSS). Generally, the four most used worldwide databases are World Income Inequality Database (WIID), Standardized World Income Inequality Database (SWIID), the data sets from the World Bank, or Deininger and Squire database (DS), representing 11%, 11%, 10%, or 3% of the estimates, respectively. The data from the World Bank are mainly from the World Development Indicators database obtaining Gini coefficients for 217 countries without specifying which type of income and data sources are based on (Fischer 2009). The WIID database is designed by the United Nations University World Institute for Development Economics Research (UNU-WIDER) and obtains data for 161 countries between 1867 and 2006, but many incomplete country-year observations, and Ginis based on different definitions and sources (Jenkins 2015).

The Deininger & Squire database is part of the WIID database and should provide high-quality data on the Gini coefficient fulfilling certain criteria defined by Deininger & Squire (1996). Such as that they need to be based on household surveys, that its population sample ought to represent the whole country average, and that the measure of income inequality ought to be composed of self-employment, non-wage revenues, and other various income sources. The Standardized World Income Inequality Database (SWIID) by Frederick Solt obtains standardized net income Gini data for 173 countries between years 1980 and 2010 without missing country-year observations and is composed of the WIID itself, Eurostat, and other databases, which is why many researchers prefer the SWIID database over the WIID (Jenkins 2015). Nevertheless, researchers vary in their opinions on which database is better for which case. For example Jenkins (2015) states that the WIID is a better option over the SWIID since it provides more credible data. Additionally, researchers also chooses databases providing data just for Europe (the Eurostat database) or for OECD countries (the OECD database), used by 7% and 18% of all estimates, respectively.

Data characteristics

We also control for the number of observations and years used to estimate the income inequality effect on happiness and denote them by the variables data size and data length, respectively. Despite the possibility of being correlated with the standard error, the variables data size and length give additional information to our model and possibly account for small-sample bias or time trend. Moreover, to control for data characteristics further, we added the age of the data used in the primary studies by incorporating the data midpoint variable represented by the mean year of the time period used by researchers. Since only the logarithm of the mean year resulted in a variable with almost zero standard deviation, we decided to adjust the variable with respect to a base year, in our case, the earliest mean year of the time period used by researchers.

We also found it important to add variable representing the number of countries since it could be an important source of heterogeneity for our data since more than two-thirds of our data vary in being for 2 to 166 countries. Additionally, we have also decided to control for the three subsets of data with respect to how many countries their data are based on. These subgroups needed to be examined further since the means of partial correlation coefficients for these subgroups differed significantly as presented in the Table 3.2. Thus, we control for a study being conducted just for one country, representing 37% of our estimates. The subgroup of estimates based on data for more than 50 countries, with the maximum being 166, represents 38% of all estimates. The reference group being the estimates based on data from 1 to 50 countries.

Additionally, we also differentiated between micro and macro level studies, based on how the researchers in their studies approached the happiness measurement. All our primary studies use subjective well-being measures based on individual responses to questions about their happiness or life satisfaction, however, some researchers also include the income inequality of the country of residence as an individual variable (Berg & Veenhoven 2010). This technique significantly increases the number of observations in contrast to macro-level studies, but the income inequality variable still signifies characteristics of the nation. The reference group being the macro-level studies.

Structural variation

In our meta-analysis, it is important to consider a possible variation of the income inequality effect on happiness across countries and geographical areas that cultural differences could cause. Therefore, we need to examine whether geography causes a systematic difference in the estimated income inequality effect on happiness. To account for possible cross-country heterogeneity, we included a number of dummies for the countries with the highest frequency of estimates, such as the United States, Germany, Japan, and China representing 5%, 3%, 6%, and 15% of estimates, respectively. We also added controls for estimates being conducted just for some parts of the world. Mostly represented groups were Europe and Asia, with 32% and 22% of estimates, accompanied by 38% estimates being worldwide.

Additionally, we have added dummy variables signifying if the estimate is for emerging or transition country or countries representing 24% of estimates. Since their level of development and different history of economic growth might vary compared to the developed countries representing 37% of estimates. As a result, citizens of emerging or transition countries might have a different view on the happiness-income inequality relationship. Since from the Table 3.2, we can see that the mean reported estimates transformed to partial correlation coefficients for emerging & transition countries may vary from the estimates for developed. Such as Helliwell & Huang (2008), who found negative impact of income inequality on well-being in developed countries and a positive effect in developing countries. Thus, we decided to include this dummy variable into our meta-regression model to discover if it is still the case after controlling for other characteristics of our data. Next, we have also decided to add two control variables for Western and non-Western countries representing 10% and 6% of estimates since these groups of countries might obtain some similar characteristics unobservable by prior division. Such as Hajdu & Hajdu (2014); Ravazzini & Chávez-Juárez (2018); Schneider (2019), who analyze the relationship between subjective well-being and income inequality separately for Western and Eastern Europe, or Verme (2011) for Western and non-Western world. Again, the reference group for these sets of dummy variables is the estimations based on both of these two groups of countries.

We also introduced the dummy variables for the subsets of poor and wealthy individuals to the meta-regression model. They represent only 3% and 4% of estimates. Nevertheless, they represent the most frequently used subset throughout the literature on the relationship between income inequality and happiness. As the differences in the magnitude of happiness-income inequality effect for poor and wealthy individuals have also been discussed by Verme (2011); Clark (2003); Wang *et al.* (2015); Helliwell & Huang (2008); Oshio & Kobayashi (2011); Du *et al.* (2019); Nguyen *et al.* (2015); Yu *et al.* (2019); Ravazzini & Chávez-Juárez (2018). Many researchers, such as Graham & Felton (2006); Oishi *et al.* (2011); Alesina *et al.* (2004); Hajdu & Hajdu (2014), have argued that income inequality has different effects on the happiness of wealthy individuals and the happiness of poor individuals, supporting the relative deprivation theory. Also, Roth *et al.* (2017) found out that higher income inequality is detrimental only for the poor and the middle class.

We also collected the estimates for subgroups of females and males or individuals of rural or urban residence. Nevertheless, their number was not accountable to control for them in our meta-analysis. Namely, for example, Alesina *et al.* (2004) also estimated the regression for males and females and for the left-wing and right-wing group. Hajdu & Hajdu (2014) similarly to Alesina *et al.* (2004) also regress for left-wing and right-wing group separately. Additionally, studies by Sanfey & Teksoz (2007); Clark (2003) and Oshio & Kobayashi (2011) have also estimated the income inequality effect on subjective well-being for females and males separately. As well as Wang *et al.* (2015); Ding *et al.* (2020); Yan & Wen (2020); Yu *et al.* (2019); Cheung (2016), in their studies analyze the happiness-income inequality link for urban residents and rural residents separately.

Estimation characteristics

Across primary studies, researchers use different methods for estimating the happiness-income inequality relationship. We control for six estimation techniques in our meta-regression model: OLS, Logit, Probit, FE, RE, and Multilevel. Both ordered logit and multilevel linear estimation model are among most commonly used techniques, applied by approximately one-third of our collected estimates. Followed by ordinary least squares, fixed effects, ordered probit, and random effect with a frequency of use 24%, 22%, 8%, and 5% of estimates, respectively. Additionally, we also controlled for the distinction between country-level and regional-level, which lies in if the researchers decided to explore the relationship between happiness and income inequality within the country or analyze the country or number of countries. Particularly, it depends on whether the Gini coefficients representing the income inequality measure are country-level or regional-level, including province-level, county-level, or any other area-level lower than country-level. More than two-thirds of the estimates are based on country-level data, and less than one-third is based on regional-level data. We decided to control also for regional-level data, since few studies such as Alesina *et al.* (2004); Schröder (2018); Grosfeld & Senik (2010) despite analyzing the relationship between subjective well-being and income inequality only for one country, still use country-level Gini to estimate the income-inequality effect on happiness.

Macroeconomic effects

Researchers examining the relationship between happiness and income inequality often control for several macroeconomic characteristics of the country, region, or province, depending on the data. Among the most frequently used economic indicators belongs gross domestic product (GDP). In more than half of our estimates, researchers chose to use the GDP variable in their models to measure the impact of income inequality on happiness. The importance of GDP variable illustrates nicely Berg & Veenhoven (2010), whose results turned from negative correlation between life satisfaction and income inequality to positive if GDP is controlled for. Although the vast majority of researchers, such as Mikucka *et al.* (2017); Beja (2014) included precisely GDP as a control variable in their models, some researchers such as Haller & Hadler (2006) controlled for GNP or Helliwell & Huang (2008) for GDP per capita, which we have also included into our variable. Other possibly essential determinants of the region or country we also decided to control for are unemployment, inflation, and income. Authors of 18%, 12%, and 8% of estimates respectively account for them in their regression.

With 3% and 7% of estimates, freedom and governmental quality variables are among the less popular determinants of country, region, or province. Primary studies used various forms of freedom variable, some studies used the decision freedom and political freedom (Haller & Hadler 2006) or some civil liberties (Gruen & Klasen 2012). Furthermore, some researchers (5% of estimates) such as Schwarze & Härpfer (2007); Hajdu & Hajdu (2014) controlled for inequality reduction, characterized as the percentage change between net and gross income inequality, calculated as Gross Gini - Net Gini divided by Gross Gini. Other characteristics occurring in several models estimating the relationship between happiness-income inequality were domestic violence ratio (Kollamparambil 2020), poverty (Fischer 2009), crime (Alesina *et al.* 2004; Kollamparambil 2020), perceived fairness (Oishi *et al.* 2011; Yu *et al.* 2019) or relative inequality of opportunity (Ravazzini & Chávez-Juárez 2018) and others. Although, we have not included them in our regression model since not enough studies controlled for them.

Microeconomic effects

Moreover, while studying the relationship between happiness and income inequality, researchers often control many individual characteristics in their models. Age and gender are two of the most widely used essential individual characteristics, with 77% and 76% of all the estimates model control for these variables, respectively. Variable age being sometimes divided into various subgroups, such as in the case of Gruen & Klasen (2012) and Oshio & Kobayashi (2011). We selected age and gender as important control variables since several researchers, such as Sanfey & Teksoz (2007); Ding *et al.* (2020); Tomioka & Ohtake (2004), have shown that females are happier than males. They have also shown that the age variable follows a U-shape pattern with the lowest level at approximately 45 years old, which is why several researchers also controlled for age squared variables in their model. Followed by a reported individual or household income, authors of more than 78 % of estimates realize that the amount of income closest to the individual level might indeed affect the happiness-income inequality relationship. Researchers use income variables in various forms, such as in the logarithm (Gruen & Klasen 2012), expressed as a percentage of the average income (Hajdu & Hajdu 2014), some uses income groups (Sanfey & Teksoz 2007). Moreover, authors of the 21% of the estimates also control for relative income, such as Ding *et al.* (2020). Relative income could also play an important role in the income inequality perception, because of the previously described theory of social comparison. Next, 73% of estimates also includes the variable or variables concerning education status, since often researchers divide the education status into numerous levels of the education system (high school, college, university) as Yu *et al.* (2019), or similarly years spend of schooling as Wu & Li (2017).

Employment and marital status, which 60% and 65% of estimates use, respectively, are also among the individual characteristics considered by researchers as one of the most significant and potentially influencing the happiness-income inequality link. Additionally, we have also analyzed the employment status control variable in more detail. Since most of our 53 primary studies use at least two categories of employment status, and approximately one-fourth of estimates account for at least six categories. The six most used categories of employment status are: employed, student, unemployed, self-employed, retired, and home with frequencies 51%, 24%, 60%, 25%, 29%, and 24% of all the estimates, respectively. As a marital status variable, some estimates used just one dummy variable (Nguyen *et al.* 2015), others used more, such as single and married (Wang *et al.* 2015) or married, divorced, separated and widowed (Haller & Hadler 2006; Delhey & Dragolov 2014).

Other relevant personal characteristics for which researchers accounted for are religion, political status, health status, and race with a frequency of 29%, 28%, 24%, and 10% of estimates. Researchers as authors of the one-third estimates also differ by how they defined the religion-related variable. Some of them just incorporated into their model a dummy signifying if the individual is religious or not (Cheung 2016), few of them also incorporated concrete variables such as Christian or Muslim (Joshanloo & Weijers 2016).

Regarding the race variable, similarly, some included into their regression just one dummy variable, such as Black (Kollamparambil 2020), others included several variables such as Black, Asian, Hispanic, Hawaiian or Pacific Islander, Native American or Multiracial (Cheung 2016). The political status control variable also includes the communist party member variable, which is involved in the models of many researchers analyzing the happiness-income inequality in China such as Ding *et al.* (2020); Zhang & Churchill (2020); Jiang *et al.* (2012); Wang *et al.* (2015). We control for also the health variable. Some researchers controlled for health just by one variable, such as Kollamparambil (2020) using good health variable. Others use division into groups, such as Nguyen *et al.* (2015) uses severe, medium or mild health condition or Hajdu & Hajdu (2014) uses from very good to bad health variable.

Additional individual characteristics, which researchers also controlled for, are regarding the individual perception of society. The two most common variables were perceived trust in people and social mobility with 33% and 4% of estimates, respectively. According to one-third of researchers, such as Mikucka *et al.* (2017), the perceived trust in society could play an important role in the happiness-income inequality estimation. Some researchers also called this variable social trust (Yan & Wen 2020) or general trust (Oishi *et al.* 2011) and many researchers used the notion social capital (Oshio & Kobayashi 2010; 2011; Fischer 2009). These variants have a similar meaning, which is why we have combined them into one control variable. Both trust in people and perceived social mobility are used in studies such as by Fischer (2009); Schalembier (2019). Among researchers who found social mobility important while explaining the income inequality-happiness link for all socio-economic groups belongs Ravazzini & Chávez-Juárez (2018) or Graafland & Lous (2018). We control for the perceived trust in people variable and social mobility variable since relatively significant branches of the relevant literature explain the income inequality effect on subjective well-being using percieved trust or mobility.

The various primary studies used in their models on estimating the happiness-income inequality effects also residential-based individual characteristics. The three most used are residential status, the number of children, and household size with the frequency of 21%, 22%, and 16%, respectively. The latter two are self-explanatory, but the residential status control variable most often indicates if the individual lives in rural areas or urban areas, such as Rodríguez-Pose & Maslauskaite (2012) or Du *et al.* (2019). Also, researchers who focus on analyzing the happiness-income inequality relationship for China often used a control variable called Hukou, which means migrants without urban household registration identity (Zhang & Churchill 2020). Such as Jiang *et al.* (2012), who found out that in China, individuals report lower subjective well-being when income inequality relates to individuals' Hukou identity irrespective of the residency status. We decided to include this control variable, although it is only China-relevant, because of the significant number of all estimates (13%) uses this variable in their model.

Publication characteristics

We inspired by a number of modern meta-analyses such as Zigraiova & Havranek (2016); Havranek *et al.* (2018); Havranek & Irsova (2017) and also accounted for publication characteristics of the primary studies to detect even more for the discrepancies among all 53 studies and 898 estimates. First, we included the publication year variable in the meta-regression model because there is always the possibility of new methodological innovation or other improvements over time that might affect the results of the happiness-income inequality relationship and weren't previously accounted for. For the publication year, we selected a similar approach as with the data midpoint variable. We took the publication year variable with respect to the base year, the earliest publication year of our sample.

Secondly, we analyzed the number of citations of the particular studies in Google Scholar per year to reflect how often the study is used as a reference in the literature. Thirdly, we used the recursive discounted impact factor from RePEc to further account for the study quality and other information on publication status since the peer-review process. In order to be able to provide variable impact factors for the studies published in journals not included in the RePec ranking, we have calculated the impact factor from the SJR ranking but adjusted it to RePec ranking scale.

As we now presented in Table 3.1, during the process of data collection, we managed to collect almost 80 characteristics from all 53 primary studies included in the meta-analysis. We aim to run a regression with the partial correlation coefficient as the dependent variable and all the aspects of data, estimation, and publication as independent variables. Nevertheless, such a regression with almost 80 explanatory variables described above would most probably contain many redundant variables because we do not know which set of variables is the most relevant for the relationship between income inequality and subjective well-being. Since the number of additional explanatory variables collected from the happiness-income inequality literature is very high, it is likely to be difficult to determine which variables should be included in the resulting model, so we face substantial model uncertainty.

In order to resolve this model uncertainty problem, we will use the most popular and efficient tools, which are called the model averaging techniques. These techniques are based on regressing all possible 2^{78} models with different variable combinations and then assigning weights to models so that better-specified models receive the larger weights. The averaging techniques we apply in this meta-analysis are the Bayesian Model Averaging technique (BMA) and the Frequentist Model Averaging (FMA). The BMA technique is the most popular and most frequently used model averaging technique in recent meta-analyses, such as by Zigraiova & Havranek (2016); Havranek *et al.* (2018); Havranek & Irsova (2017); Gechert *et al.* (2021). The BMA resolves the model uncertainty nicely since it estimates models for all possible variable combinations of X_j from the Equation 5.1 and computes a weighted average over all of them. With the BMA approach, we aim to estimate the size of the effect, which each variable has on the happiness-income inequality relationship to help determine the design of future studies.

The Bayesian Model Averaging (BMA) technique uses several important statistical measures, such as posterior model probability, posterior inclusion probability, weighted posterior mean, weighted posterior standard deviation, and variance, which we will know introduce:

- *Posterior model probability* (PMP) is analogous to information criteria in classical frequentist econometric. The PMP is assigned to each model, where it measures its performance compared to other models. The PMPs also represent the weights, using which the results from all regressions are averaged to obtain the resulting statistics.

- *Posterior inclusion probability* (PIP) is similar to the statistical significance. The PIP is the posterior probability of the particular variable being included in the model. It could also be defined as the sum of PMP for all models, including the particular variable. The higher the PIP, the more important is the variable in explaining the heterogeneity, so the PIP signifies how important is the variable in explaining the data.

- *Weighted posterior mean* (PWM) is analogous to the model average parameter estimate. The BMA calculates PWMs across models based on individual model estimates weighted by their posterior model probabilities. Even the models without the particular variable are included in the average with zero parameter estimate.

- *Weighted posterior standard deviation* is analogous to the standard error. *Weighted posterior variance* is calculated based on the weighted average of the individual model's estimated variances as well as on the weighted variance in β_j estimates across various models. As a result, despite possibly having a highly precise estimate in all models, considerable uncertainty about the parameters can be discovered because of different estimates across models.

The Bayesian Model Averaging (BMA) technique approach is based on Bayes' theorem, the law of total probability, and taking the unknown model parameters as random variables. Hereby, we will describe the BMA processes, as also described by Hoeting *et al.* (1999). Firstly, we denote:

- D = data, K = total number of explanatory variables in the model,
- N = number of possible models, = 2^K potential model specifications,
- M = set of considered models from M_1 to M_K,
- $p(M_k|D)$ = likelihood of model M_k being correct prediction model given data D, i.e. prior probability of M_k being the true model also called as posterior model probability (PMP),
- i = parameter of interest, e.g. future observable or model parameter,
- $p(i|D)$ = posterior distribution of i given observed data D,
- $p(i|M_k, D)$ = posterior distribution of i under model M_k given data D.

The BMA results are likely to reflect the true uncertainty generally, thanks to enabling to incorporate the model's uncertainty into inference. The BMA starts with the following equation:

$$p(i|D) = \sum_{k=1}^{K} p(i|M_k, D)p(M_k|D) \tag{5.2}$$

The Equation 5.2. of posterior distribution represents an average of posterior distributions under each model of the M set of considered models weighted by their PMP, where for any model space, the sum of these weights ($p(M_k|D)$)

is equal to one (Zou *et al.* 2012). The posterior model probability for model M_k is based on previously mentioned Bayes' theorem:

$$p(M_k|D) = \frac{p(D|M_k)p(M_k)}{p(D)} = \frac{p(D|M_k)p(M_k)}{\sum_{m=1}^{K} p(D|M_m)p(M_m)}, \tag{5.3}$$

where:

$$p(D|M_k) = \int ... \int p(D|\theta_k, M_k)p(\theta_k|M_k)d\theta_k. \tag{5.4}$$

Denoting the variables form Equation 5.3 and 5.2:

- $p(D|M_k)$ = corresponding marginal model likelihood of model M_k,
- θ_k = vector of parameters of model M_k,
- $p(\theta_k|M_k)$ = prior density of θ_k under model M_k,
- $p(D|\theta_k, M_k)$ = likelihood in conventional form.

Finally, we can define the posterior mean and variance based on the BMA process as follows:

$$E(i|D) = \sum_{k=1}^{K} E(i|D, M_k)p(M_k|D) \tag{5.5}$$

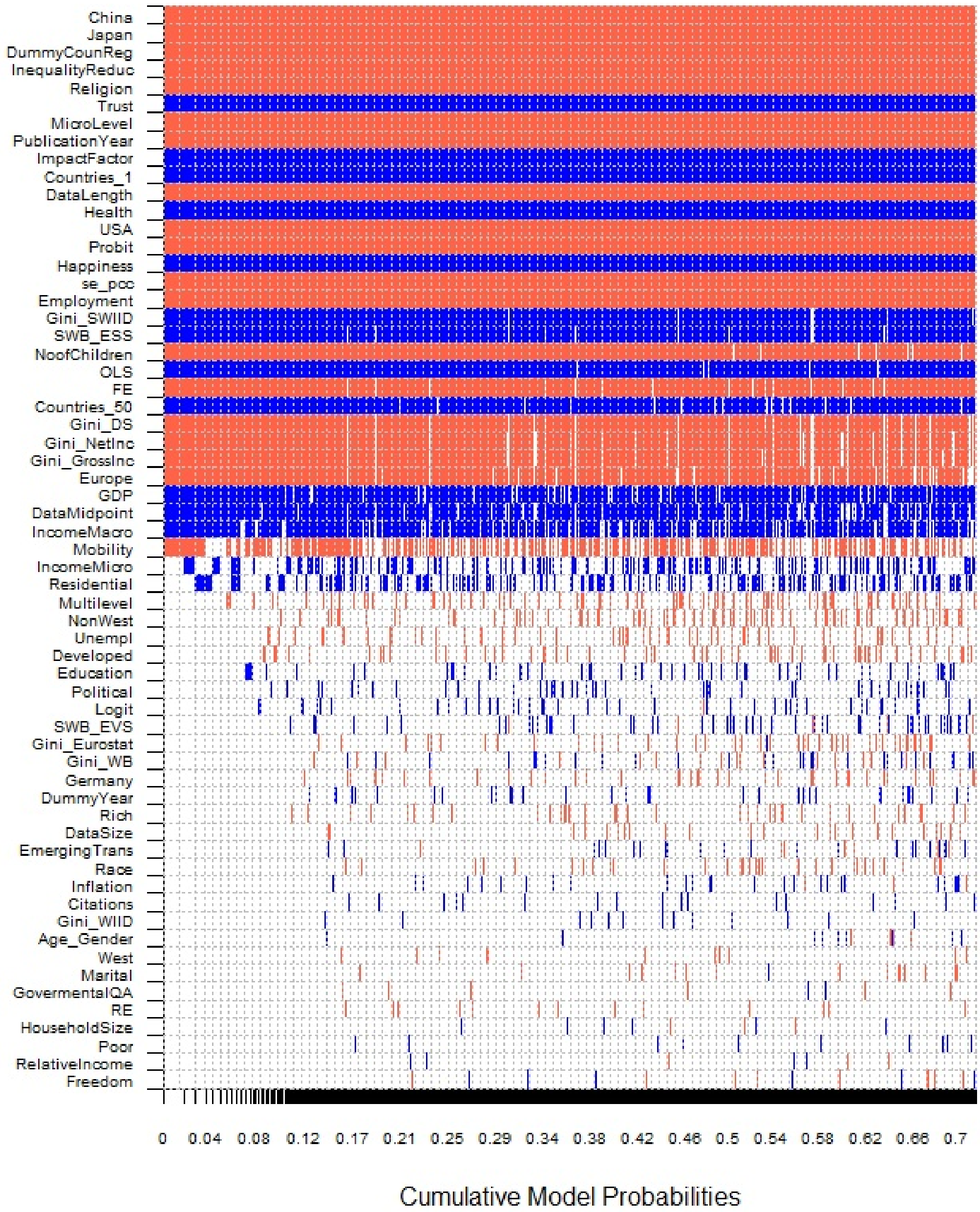
$$Var(i|D) = \sum_{k=1}^{K}(Var(i|D, M_k) + E(i|D, M_k)^2)p(M_k|D) \tag{5.6}$$

In practice, we decided to employ the Monte Carlo Markov Chain algorithm, which focuses on the most convenient models with the highest PIPs in order to make the estimation of all 2^K models feasible (2^{78} in our case). We performed the BMA procedure and the rest of all computations in our meta-analysis in the R software environment. For the BMA we used the Bayesian model selection (bms) package by Zeugner *et al.* (2015), where we selected following arguments: burn = 1 000 000, iter = 2 000 000, g = "UIP", mprior = "dilut", nmodel = 50000, mcmc = "bd" and user.int = FALSE.

Thus, we set the number of iterations not stored to compute PMPs (burn) to one million and the general number of iterations to be sampled (iter) to two million. Next, we set that the number of best models for which information is stored to fifty thousand models. We used the Markov Chain Monte Carlo (mcmc) sampler's birth-death (bd) algorithm, which causes the randomly chosen variable to be added or dropped depending on whether it is already in the model. As the g-prior (g) for the regression coefficients, described as the weight of the prior on individual coefficients, we selected the most common g-prior called unit information prior (UIP). The UIP provides the same and small importance to each coefficient since it reflects truthfully the number of observations, which is in our case 868. As the prior on model probability, we have not used the baseline uniform model prior, assigning each model the same prior probability. Because of concerns regarding the very high number of control variables, to prevent multicolinearity, we have decided to use the dilut model prior, which can compensate for redundancy between model classes (George 2010). The results of BMA when alternative priors are used are presented in the Figure 5.2 and Appendix C.

The Bayesian Model Averaging estimation results, on the winsorized sample at 1% on both distribution's sides, are graphically represented in the Figure 5.1. The horizontal axis of the Figure 5.1 depicts the cumulative posterior model probabilities. So from the top to the bottom of the graph, the variables are ranked with respect to their relevance in the regression model from the vari-

Figure 5.1: Model inclusion in Bayesian Model Averaging



Notes: The figure depicts the results of BMA analysis for analyzing the effect of income inequality on happiness with winsorized data at 1% level on both distributions' sides. The vertical axis = depicting explanatory variables sorted from the one with the highest posterior inclusion probability at the top to the lowest at the bottom. The horizontal axis = depicting the cumulative posterior model probabilities. The blue (darker in greyscale) colored cells = showing the estimated effect of a relative variable is positive. The red (lighter in greyscale) colored cells = showing the estimated effect of a relative variable is negative. White color - showing that the variable is not included in the model.

able with the highest PIP to the variable with the lowest PIP. The vertical axis of the figure depicts the regression of explanatory variables respectively to their relevance in the model. From the Figure 5.1 can also be observed if the particular regression explanatory variable has a positive or negative effect on the dependent variable, which is, in our case, subjective well-being. If the coefficient of the particular variable listed on the vertical axis is positive, the cells in line representing the variable have blue color (darker in greyscale), and if it is positive the cells are red (lighter in greyscale). Furthermore, unlike the red and blue-colored cells, the white-colored cell reflects the component that was not used in the regression model.

As can be seen in the Figure 5.1, approximately half of the displayed explanatory variables appear in the best models, as well as that the signs of the estimated parameters are robust when including other controls, since, within each row, the sign of the variable remains the same. The full list of variables and their description are displayed in the Table 5.1. In order to avoid the dummy variable trap, we have used the following variables as the reference group, thus we did not include them into the BMA regression: Life satisfaction, Countries 1-50, Macro level, Country level. Additionally, because of the high correlation among the variables we have excluded from the BMA regression, the following variables: Number of countries, Regional level, SWB: WVS database, Gini: OECD database, Worldwide, SWB: 10-11, 5-7, 3-4 point scale. We have also excluded Hukou, Asia, and SWB & Gini: CGSS data since they are highly correlated with the China variable. Also, we have merged Age and Gender variable since most of our primary studies use either none of them or both. The correlation matrix of the remaining 62 regression explanatory variables is presented in Appendix B in Figure B.1.

Table 5.2: Explaining the heterogeneity in the effect of income inequality on happiness using BMA and Frequentist check

	BMA			FC		
Response variable	PIP	PM	PSD	Coef	SE	p-val
(Intercept)	**1.000**	0.355	NA	0.360	0.084	**0.000**
se_pcc	**1.000**	-1.320	0.278	-1.365	0.640	**0.033**
Subjective well-being specifications						
Happiness	**1.000**	0.046	0.010	0.044	0.018	**0.013**
SWB: EVS data	0.079	0.001	0.006			
SWB: ESS data	**0.989**	0.082	0.021	0.083	0.017	**0.000**
Income inequality specifications						
Gini: Net Income	**0.945**	-0.046	0.016	-0.044	0.012	**0.000**
Gini: Gross Income	**0.937**	-0.042	0.016	-0.041	0.013	**0.002**
Gini: WB data	0.077	0.001	0.008			
Gini: SWIID data	**0.995**	0.039	0.011	0.034	0.012	**0.005**
Gini: WIID data	0.034	0.000	0.002			
Gini: DS data	**0.965**	-0.064	0.020	-0.066	0.034	0.056
Gini: Eurostat data	0.078	-0.002	0.008			
Data characteristics						
Data midpoint	**0.893**	0.085	0.040	0.090	0.064	0.160
Data length	**1.000**	-0.068	0.013	-0.070	0.017	**0.000**
Data size	0.048	-0.000	0.003			
Micro level	**1.000**	-0.162	0.024	-0.162	0.056	**0.004**
1 country	**1.000**	0.083	0.014	0.085	0.018	**0.000**
50+ countries	**0.970**	0.038	0.013	0.038	0.016	**0.016**
Structural variation						
Europe	**0.938**	-0.036	0.014	-0.043	0.015	**0.003**
Germany	0.073	-0.002	0.011			
USA	**1.000**	-0.122	0.024	-0.128	0.032	**0.000**
China	**1.000**	-0.214	0.023	-0.210	0.030	**0.000**
Japan	**1.000**	-0.176	0.021	-0.177	0.035	**0.000**
Developed	0.109	-0.001	0.005			
Emerging&Transition	0.048	0.001	0.006			
Western	0.028	-0.000	0.002			
Non-Western	0.134	-0.004	0.011			
Poor	0.023	0.000	0.002			
Rich	0.055	-0.001	0.004			
Estimation characteristics						
OLS	**0.986**	0.034	0.009	0.036	0.008	**0.000**
Logit	0.095	0.001	0.006			
Probit	**1.000**	-0.065	0.013	-0.068	0.013	**0.000**
Multilevel	0.168	-0.003	0.008			

Continued on next page

Table 5.2: Explaining the heterogeneity in the effect of income inequality on happiness using BMA and Frequentist check (continued)

		BMA			FC	
Response variable	PIP	PM	PSD	Coef	SE	p-val
FE	**0.971**	-0.037	0.012	-0.038	0.014	**0.003**
RE	0.026	-0.000	0.002			
Area dummy	**1.000**	-0.037	0.007	-0.036	0.008	**0.000**
Year dummy	0.070	0.001	0.003			
Macroeconomic effects						
GDP	**0.934**	0.018	0.007	0.018	0.006	**0.001**
Income macro	**0.860**	0.035	0.018	0.038	0.015	**0.015**
Inflation	0.044	0.001	0.004			
Unemployment	0.120	-0.002	0.006			
Government quality	0.025	-0.000	0.002			
Inequality reduction	**1.000**	-0.124	0.018	-0.120	0.025	**0.000**
Freedom	0.022	0.000	0.002			
Microeconomic effects						
Age&Gender	0.030	0.000	0.002			
Race	0.046	-0.001	0.004			
Education	0.101	0.001	0.005			
Employment	**1.000**	-0.027	0.007	-0.023	0.005	**0.000**
Residential	0.343	0.006	0.010			
Marital	0.026	-0.000	0.001			
Income micro	0.346	0.006	0.009			
Relative income	0.022	0.000	0.001			
Religion	**1.000**	-0.063	0.010	-0.061	0.014	**0.000**
No of children	**0.988**	-0.033	0.010	-0.033	0.012	**0.006**
Household size	0.023	0.000	0.001			
Health	**1.000**	0.034	0.007	0.037	0.006	**0.000**
Trust	**1.000**	0.067	0.009	0.067	0.014	**0.000**
Political	0.098	0.002	0.005			
Mobility	**0.558**	-0.019	0.019	-0.036	0.010	**0.000**
Publication characteristics						
Publication year	**1.000**	-0.178	0.034	-0.186	0.061	**0.002**
Citations	0.036	0.000	0.002			
Impact factor	**1.000**	0.142	0.025	0.145	0.027	**0.000**
Observations		868		868		
Studies		53		53		

Notes: The table shows the Bayesian model averaging (BMA) results on the left-side and Frequentist check results the right-side. PIP = Posterior Inclusion Probabilty, PM = Posterior Mean, PSD = Posterior Standard Deviation, Coef = OLS coefficient, SE = Standard Error, p-val= P-value. PIPs above 0.5 are highlighted in bold. The frequentist check includes only variables that have a PIP higher than 0.5.

The Bayesian Model Averaging estimation results are also presented numerically in the left-hand panel of Table 5.2. We performed a frequentist check as a robustness check of our baseline BMA approach, where we include just the variable for which we obtained the PIPs higher than 50% in the BMA, which is the case of 31 variables meta-analysis. As a frequentist check, we used OLS estimation with robust standard errors clustered at the study level. The results of the frequentist check estimation are presented in the right-hand panel of Table 5.2. From the results in the Table 5.2, we can see that according to the frequentist check, all explanatory variables from the BMA except for data midpoint variable and Gini: DS database are statistically significant at 5 percent level. Furthermore, that 70% of the variables with PIP higher than 0.5 are statistically significant even at one percent level. We have decided to measure the significance of all our independent variables, according to Jeffreys (1998); Eicher *et al.* (2011): if PIPs higher than 0.5, it provide significant information about the variation of the variable. In detail, if PIP is between 0.5 and 0.75, it provides weak significance, if between 0.75 and 0.95 substantial one, and if between 0.95 and 0.99 a strong significance, higher than 0.99 is called decisive.

Except for Bayesian Model Averaging and Frequentist check, we additionally also apply the Frequentist Model Averaging (FMA) as a robustness check for the results of these two previously applied methods. The FMA is an alternative model averaging technique helping to address model uncertainty issue, among which benefits belongs better model interpretation. The FMA includes all 62 controlling variables in its analyses, and for its performance, we use the R software environment. The results of the FMA estimation are presented in the Table 5.3. From Table 5.3, we can see that the results based on Frequentist Model Averaging technique are generally in line with the previous results based on Bayesian Model Averaging and Frequentist check technique. Similarly to the BMA, the FMA also stands on the idea of restricting the number of estimated models, but for which the FMA approach uses Mallow's model averaging estimator and orthogonalization of the covariate space according to

Amini & Parmeter (2012), so the weights for model averaging are chosen based on the Mallow's criteria.

Table 5.3: Explaining the heterogeneity in the effect of income inequality on happiness using Frequentist Model Averaging

Response variable	Coefficient	Stand.error	p-value
(Intercept)	0.381	0.059	**0.000**
se_pcc	-1.635	0.311	**0.000**
Subjective well-being specification			
Happiness	0.056	0.010	**0.000**
SWB: EVS data	0.019	0.014	0.163
SWB: ESS data	0.124	0.025	**0.000**
Income inequality specifications			
Gini: Net Income	-0.062	0.019	**0.001**
Gini: Gross Income	-0.059	0.019	**0.002**
Gini: WB data	-0.009	0.016	0.594
Gini: SWIID data	0.063	0.016	**0.000**
Gini: WIID data	0.005	0.008	0.556
Gini: DS data	-0.078	0.020	**0.000**
Gini: Eurostat data	-0.004	0.020	0.824
Data characteristics			
Data midpoint	0.116	0.035	**0.001**
Data length	-0.073	0.014	**0.000**
Data size	-0.015	0.008	0.074
Micro level	-0.166	0.026	**0.000**
1 country	0.083	0.018	**0.000**
50+ countries	0.028	0.014	**0.044**
Structural variation			
Europe	-0.052	0.013	**0.000**
Germany	0.029	0.021	0.172
USA	-0.113	0.023	**0.000**
China	-0.278	0.029	**0.000**
Japan	-0.201	0.024	**0.000**
Developed	-0.007	0.010	0.505
Emerging&Transition	0.020	0.018	0.279
Western	-0.006	0.010	0.522
Non-Western	-0.057	0.023	**0.012**
Poor	0.003	0.011	0.792
Rich	-0.012	0.011	0.284
Estimation characteristics			
OLS	0.030	0.014	**0.029**
Logit	0.008	0.015	0.583

Continued on next page

Table 5.3: Explaining the heterogeneity in the effect of income inequality on happiness using Frequentist Model Averaging (continued)

Response variable	Coefficient	Stand.error	p-value
Probit	-0.061	0.018	**0.001**
Multilevel	-0.005	0.015	0.718
FE	-0.031	0.011	**0.006**
RE	-0.013	0.014	0.350
Area dummy	-0.040	0.009	**0.000**
Year dummy	0.007	0.008	0.390
Macroeconomic effects			
GDP	0.016	0.006	**0.009**
Income macro	0.070	0.015	**0.000**
Inflation	0.026	0.016	0.098
Unemployment	-0.024	0.014	0.094
Government quality	0.001	0.013	0.958
Inequality reduction	-0.156	0.020	**0.000**
Freedom	0.003	0.016	0.874
Microeconomic effects			
Age& Gender	-0.001	0.018	0.959
Race	-0.019	0.013	0.157
Education	0.001	0.012	0.905
Employment	-0.028	0.009	**0.001**
Residential	0.022	0.010	**0.022**
Marital	0.000	0.014	**0.000**
Income micro	0.015	0.009	0.087
Relative income	0.002	0.009	0.856
Religion	-0.082	0.012	**0.000**
No of children	-0.020	0.012	0.087
Household size	-0.006	0.012	0.646
Health	0.026	0.008	**0.001**
Trust	0.069	0.010	**0.000**
Political	0.020	0.011	0.084
Mobility	-0.024	0.014	0.075
Publication characteristics			
Publication year	-0.171	0.036	**0.000**
Citations	0.001	0.011	0.917
Impact factor	0.170	0.025	**0.000**
Observations	868		
Studies	53		

Notes: The table shows the Frequentist Model Averaging (FMA) results. In FMA, the optimal weights for models are chosen based on the Mallow's averaging based on orthogonalization of the covariate space.

Looking at our results from all three specifications and estimation methodologies, first of all, we can conclude that our results of publication bias presented in the previous chapter remain robust even after controlling for all 62 explanatory variables. Since as can be seen from Table 5.2, the variable representing standard error of the partial correlation coefficient, corresponding to the publication bias, is found as one of the most effective variables in explaining the heterogeneity of the relationship between income inequality and subjective well-being.

Next, since we have a large number of variables, we have highlighted the most important variables for each category of variables that provide significant information about the variation of the relationship between income inequality and subjective well-being (SWB). Thus, for each group of variables as presented in Table 5.1, we comment on the results of the Bayesian Model Averaging (BMA), Frequentist check, and the Frequentist Model Averaging (FMA) generally. And then, within each group, to have the text better structured, we point out using bullet points the most important variables, which are consistently significant based on all three techniques. Moreover, we comment on them separately in more detail because of their importance.

Subjective well-being specifications

Our results provide evidence on the systematic importance of subjective well-being specifications. According to our findings based on both model averaging techniques and the OLS-based frequentist check, the definition of our dependent variable (subjective well-being variable) has a decisive factor in determining the source of heterogeneity of income inequality effect estimates. Based on our results, the researchers who use happiness-related questions as a measure of SWB tend to obtain higher estimates than those using questions related to life satisfaction or both. Additionally, as opposed to the European Value Survey (EVS), the European Social Survey (ESS) usage for the dependent variable proved to be a significant factor for the happiness-well-being relationship yielding a more positive effect. Results significant for both model averaging approaches and the frequentist check.

- **Happiness** The choice of happiness as the subjective well-being measure suggests the estimate of income inequality on SWB to be on average 0.046 higher than when SWB based on life satisfaction is chosen. The PIP has a decisive value of 1.000. Our finding is not in line with the previous researchers since most researchers throughout fields (Frey *et al.* 2018; Ferrer-i Carbonell & Ramos 2014; Tella *et al.* 2003) use terms subjective well-being (SWB), happiness, and life satisfaction interchangeably. Also, our most cited primary study by Alesina *et al.* (2004) calls life satisfaction "happiness" throughout the study. Alesina *et al.* (2004) focuses on comparing income inequality effect on SWB between Europe and the United States. Nevertheless, Alesina *et al.* (2004) use happiness measure for the United States, but life satisfaction measure for Europe, and compare them simultaneously. As an explanation, they use high correlation of measures and availability of the data on life satisfaction measure for longer period. As far as we are concerned, we have not found in the literature any study specializing on the relationship between SWB and income inequality, which would analyze the differences between life satisfaction and happiness in more detail. Thus, our research provides an incentive for future research to focus on this possible issue.

- **SWB: ESS database** When the European Social Survey (ESS) database is used for the subjective well-being measure (SWB), the effect of income inequality on SWB is on average 0.082 higher than when other SWB measure data sources are used. The PIP has a decisive value of 0.989. This result could be potentially important for further investigation of the relationship between income inequality and SWB. Since possibly if a researcher uses the European Social Survey as a subjective well-being data source, the resulting estimate might be higher.

Income inequality specifications

Our results suggest that the choice of income group for the Gini coefficient used as an income inequality measure is significant for income inequality effect on subjective well-being, which also confirms both model averaging approaches and the frequentist check. Nevertheless, based on our results, the choice of the data source for income inequality is likely irrelevant. Since only one variable regarding the Gini coefficient's database, the Standardized World Income Inequality Database (SWIID), out of six is relevant for the relationship between income inequality and happiness, as confirmed by all three techniques consistently. Using the Bayesian model averaging and the Frequentist model averaging approach, next to the SWIID database, the high-quality database by Deininger & Squire (1996) proved to be relevant. Its usage is likely to decrease the estimated income inequality effect on SWB, as opposed to the SWIID database, which usage is associated with a higher effect.

- **Gini: Net Income, Gini: Gross Income** The inclusion of the control variables accounting for net income-based and gross income-based Gini coefficient has a substantial impact of PIP value of 0.945 and 0.937, respectively. The reported estimate yields, on average, more negative estimates by -0.046 and -0.042, respectively. In line with our research, several researchers also differentiated between net income-based Gini (also called post-governmental Gini) and gross income-based Gini (also called pre-governmental Gini). Such as Schwarze & Härpfer (2007) who compared the effects of pre- and post-government income inequality on German's happiness, using data from the SOEP from 1985 to 1998. Schwarze & Härpfer (2007) found a clear negative relationship between the post-government income inequality and subjective well-being only for poor Germans, but the negative relationship between the pro-government income inequality and subjective well-being for all income groups. Also, Fischer (2009) found his results stronger in the case of pre-transfer than post-transfer income inequality.

  Additionally, many researchers such as Roth *et al.* (2017); Verme (2011); Cheung & Lucas (2016) focused on the relationship between SWB and income inequality based on post-governmental income. According to Schröder (2018), using the net income Gini coefficients makes more sense than using the gross income Gini coefficients, as the net income distribution reflects more discrepancies in living standards. Although the Gini coefficients based on both net income and gross income are highly correlated because of their similarity, as Katic & Ingram (2018) concludes, the literature lacks consensus on which of them is preferred.

Our research concludes that most studies in the literature regarding income inequality and subjective well-being prefer the net income to gross income inequality measure. Since the Gini coefficients based on net incomes represent the disposable income, so money available for spending and saving as individual wishes. Additionally, we also showed that income inequality based on net or gross income on SWB is on average significantly smaller than the effect of income inequality based on other income groups, such as expenditure or consumption. It is also consistent with the values of mean partial correlation coefficients estimated for various types of Ginis as reported in the Table 3.2. Nevertheless, no researchers before compared the effect of income inequality based on net income, gross income, with other types of income (expenditure, consumption) on SWB, as far as we are concerned. Since we have discovered that they can, on average, systematically differ, we call for further research on this topic.

- **Gini: SWIID database** Using the Standardized World Income Inequality Database (SWIID) for the income inequality variables results in, on average, 0.039 higher effect of income inequality on subjective well-being than if other data source for Gini coefficient is used, with the PIP value of 0.995. There could be several reasons for it. As claimed by Livani (2017); Cheung (2018), the SWIID database is the most convenient database for income inequality measure since it is better suited to cross-national research because of greater coverage and three to eight times better comparability than other alternative databases.

Data characteristics

Additionally, the control variables related to the data systematically affect the estimates of the income inequality effect on SWB. Since both the Bayesian model averaging and the Frequentist model averaging approach identified five of our six variables concerning data characteristics as significant, the OLS-based frequentist check confirmed the significance of four, excluding the data midpoint variable. In general, our findings point to a slight upward trend in the observed impact of income inequality on subjective well-being, as well as that estimates based on micro-level regression seem to be lower than those for macro-level regression.

- **Data Length, Data Midpoint** The variables indicating the data length calculated by the logarithm of the number of years resulted in a decisive PIP of 1.000. The posterior mean is equal to -0.068. It could be caused by many subjective well-being data surveys are not being held annually, or because the search for relevant data is demanding both for SWB and income inequality, especially for the regional data. The inclusion of variables indicating the data midpoint, calculated as the logarithm of the year with respect to the earliest year used in the sample, resulted in a substantial PIP of 0.893 and the posterior mean equal to 0.085. It denotes the importance of time since new methodological or estimation innovation and other changes over time may influence the happiness-income inequality relationship in ways that were previously unaccounted for. Additionally, Schröder (2018) and Yan & Wen (2020) claim that subjective well-being is affected more by changes of inequality over time than by long-run levels of inequality, which also supports the adaptation-level theory.

- **Micro-level** The micro-level structure of data seems to produce a significantly lower effect of income inequality on SWB than if macro-level structured data are applied. The PIP is again the highest possible with the value of 1.000, and the posterior mean is equal to -0.162. So the effect of income inequality on SWB is lower if the researchers use the individual-level subjective well-being data and include the country's or region's income inequality as an individual variable. This approach additionally also significantly increases the number of observations in contrast to macro-level studies, but the data size variable has not proved to be significant for the relationship.

- **1 country, 50+ countries** The control variable accounting for researchers analyzing only one country has a decisive effect of PIP value of 1.000. Similarly, the control variable accounting for researchers analyzing more than 50 countries has a similarly high PIP value of 0.970. The partial correlation coefficient obtained based on estimation for one country is on average significantly higher by 0.083, and based on estimation for more than 50 countries is on average higher by 0.038. For worldwide studies, the subgroup of estimates based on data for more than 50 countries should provide less biased results than the reference subgroup of estimates based on data from two to 50 countries because of being less sensitive to cross-country heterogeneity. One of the things which varies the most across studies is on which level the researchers decided to perform their analysis or how many countries they included, the latter showed to be more important for the relationship between income inequality and SWB based on our results.

Structural variation

According to our findings, the evidence that structural variation in our primary studies tends to cause significant systematic differences in the reported estimates of income inequality on happiness is mixed. Our results suggest, that differences between various subgroup such as based on the level of development of the particular analyzed countries or its location (Developed, Emerging&Transition, Western, Non-Western), or based on a wealth of individuals (Poor, Rich), were not confirmed by the Bayesian model averaging techniques as relevant. Our finding is not in line with previous research since many researchers found different results for income inequality effect on happiness for various subgroups around the world. According to Helliwell & Huang (2008), income inequality has a negative impact on well-being in developed countries but a positive effect in developing countries. Berg & Veenhoven (2010) found a strong negative relationship between income inequality and happiness for the Western world even after controlling for wealth, but a positive relationship for Eastern Europe. Alternatively, Sanfey & Teksoz (2007) showed that income inequality has a positive effect on life satisfaction in transition countries but negative in non-transition countries. Also, Beja (2014) showed that people from emerging economies are less sensitive to income inequality than people from developed ones.

Alternatively, Verme (2011) found a negative effect of income inequality on SWB for both Western and non-Western countries, but a not significant one for the latter. Also, Kelley & Evans (2017) observed that citizens of more equal societies are less happy in developing countries. The possible explanation could be that poor people in developing countries hope to move up in the income ladder in the countries with higher income inequality, supporting the tunnel theory. Although other theories, such as social comparison theory, claim that they might experience status anxiety, envy, or relative deprivation.

Furthermore, our results did not find the variables representing rich and poor subgroups of individuals relevant for the relationship between happiness and income inequality. As opposed to, for example, Hajdu & Hajdu (2014), who found out that poorer individuals generally have lower subjective well-being in case of high income inequality supposedly because of envy supporting the relative deprivation theory. Using the Gini coefficient based on the net income, Schwarze & Härpfer (2007) observed similar findings for West Germany. Additionally, Verme (2011) reports the negative effect of income inequality on the well-being of non-poor individuals, but for poor individuals, the results are inconclusive. However, our results from model averaging techniques and frequentist check differ from our estimated mean values of partial correlation coefficients for these groups as presented Table 3.2. The results presented in Table 3.2 varied significantly across subgroups and were in line with previous research Since the partial correlation coefficients for the Non-West, Emerging&Transition, and Poor subgroups were, on average, positive. In contrast to the West, Developed, and Rich subgroups, which had negative average partial correlation coefficients. These results were why we included these control variables into our heterogeneity analysis, but surprisingly none of them proved to be significant or relevant contrarily to previous research. Results for structural variation are consistent across all three techniques. Just the Frequentist Model Averaging approach finds the Non-Western variable also significant.

On the other hand, other structural differences were found relevant. Our results suggest that estimates for European countries seem to be lower than those for other countries. Our findings also support country-level differences, three out of four variables controlling for countries are significant. Individuals from the USA, China, and Japan are likely to experience a smaller effect of income inequality on happiness, consistently based on both model averaging techniques and frequentist check.

- **USA** The inclusion of the United States variable into the regression has the highest possible PIP value of 1.000. It signifies that this variable is decisive for estimating income inequality effect on subjective well-being, causing the effect to become -0.122 lower on average. This finding could be considered in line with previous research since many researchers found out that income inequality significantly reduces happiness in the United States, such as Oishi *et al.* (2011) examining this effect for the United States based on longitudinal data from 1972 to 2008.

- **USA, Europe** Nevertheless, our findings are not precisely in line with Alesina *et al.* (2004) who compared the long-run data from United States (GSS, 1972-97) and Europe (Eurobarometer, 1975-92). They found out that income inequality reduces reported subjective well-being amongst Europeans, but not so clearly amongst Americans. Based on their results, even after controlling for individual characteristics of the respondents, state or country, and year effects, the USA citizens seem to be less affected by inequality than Europeans. The possible explanation is that there is a higher perceived social mobility in the USA than in Europe. It is not in line with our research since for Europe, on average, the estimation yields a much smaller negative coefficient (-0.036) than for the USA (-0.122). Thus, we cannot support the claim that income inequality decreases Europeans' subjective well-being more than American's, based on our heterogeneity analysis. Although, our finding of mean partial correlation coefficients estimated for the USA and Europe subgroup presented in Table 3.2 is more in line with results of

Alesina *et al.* (2004). To conclude, future research should further elaborate on the difference between Europe and the USA regarding the SWB - inequality link.

- **Europe** The significance of the European variable is strong, with a PIP value of 0.983. When considering only the results for the European variable, our results rather supports previous research, since many researchers found a significant negative link between income inequality and SWB based on European data, such as Schneider (2019); Joshanloo & Weijers (2016); Hajdu & Hajdu (2014); Schalembier (2019); Alesina *et al.* (2004). The possible explanation is that in Europe, the perceived social mobility is lower, resulting in the poor not expecting to get better in the future and therefore disliking inequality, as mentioned by Alesina *et al.* (2004). Alternatively, Delhey & Dragolov (2014) founds that income inequality lowers the degree of Europeans' subjective well-being, and consider distrust and status anxiety as potential causes.

- **China, Japan** The inclusion of China and Japan variable into the regression has a PIP value of 1.000 and 1.000, signifying that these variables are significant for estimating income inequality effect on subjective well-being, causing a negative effect on average -0.214 and -0.176 lower. Our results supports previous research. Since many researchers, such as Ding *et al.* (2020); Wang *et al.* (2015); Yu *et al.* (2019), have proven that income inequality has a significantly negative impact on subjective well-being in China. Additionally, researchers such as Oshio & Kobayashi (2010; 2011); Tomioka & Ohtake (2004), have proven significant negative impact also for Japan. Moreover, Ding *et al.* (2020) and Wang *et al.* (2015) discovered in China an inverted-U-shaped relationship between income inequality and well-being, with a peak around a Gini of 0.5.

Estimation characteristics

According to our results, the estimation characteristics applied in primary studies could cause significant systematic differences in the reported estimates of income inequality on happiness on a larger scale. The variables representing usage of OLS, ordered probit, and fixed-effect provides significant information about the variation of the income inequality effect on happiness, unlike variables representing usage of ordered logit, multilevel and random-effects methods. Also, the country or regional dummy variable has decisive significance, as opposed to the year dummy. The results regarding the estimation characteristics are perfectly consistent across different model averaging approaches and frequentist check.

- **OLS, FE, Probit** The variable OLS have a decisive impact of PIP value of 0.986, similarly PIP value of strong 0.971 for fixed-effects and decisive 1.000 for ordered probit. Nevertheless, the partial correlation coefficient obtained by using the OLS is significant and tends to be about 0.047 points higher than its counterparts on average. On the other hand, the partial correlation coefficients estimated by fixed-effects and ordered probit are, on average, lower by -0.037 and -0.065 than the rest of the estimates. Thus, our results suggest that using OLS estimation is in line with higher estimates of income inequality effect on happiness, and using ordered probit or fixed effects methods systematically like to cause lower estimates of the effect compared to using of other estimation techniques.

- **Country or Regional dummy** The inclusion of country or regional dummies in the regression produces a more negative effect. This dummy is decisively significant with PIP equal to 1.000 and the posterior mean equal to -0.037. The presence of country or regional dummies in the regression signifies that country or regional effects are accounted for in the regression. Thus, this finding supports our hypothesis that distinguishing between geographical characteristics is crucial in the literature concerning the income inequality and happiness relationship, because of the possibility of capturing possible cultural differences in perceiving income inequality, as mentioned previously.

Macroeconomic effects

Other possibly important factors producing heterogeneity of reported estimates of the income inequality effect on subjective well-being are characteristics of countries or regions in which respondents reside. For macroeconomics variables, three out of seven were found significant. The inclusion of the inequality reduction variable is likely to lead to a significant decrease in the income inequality effect on subjective well-being. On the other hand, controlling for GDP and country or regional level income variable substantially increases the magnitude of the income inequality effect. Results for macroeconomic effects are consistent across all three techniques.

Thus, we have not found variables inflation and unemployment significant for the relationship between income inequality and happiness. Although previous findings such as by Tella *et al.* (2003); Engelbrecht (2009); Grosfeld & Senik (2010) confirmed that subjective-well being is influenced by inflation or unemployment significantly. Generally, many studies also consider the unemployment variable important while estimating the income inequality-happiness link. Such as Alesina *et al.* (2004), since after controlling for unemployment in their model, the negative relationship between happiness and income inequality for the United States turned insignificant.

- **Income of country or region, GDP** Both country- or regional-level income and GDP variables seem to have substantial significance with a PIP value of 0.860 and 0.934, respectively. Their inclusion into regression appears to produce, on average, 0.035 and 0.018 higher effects, respectively. Since both variables represent the indicator of the wealth and prosperity of the particular country or region, it is logical that their impact and significance for the relationship between income inequality and subjective well-being will be similar, which our results support. It could be said that our results are in line with research. The importance of wealth indicator also supported by Delhey & Dragolov (2014), and Engelbrecht (2009). According to their results, income inequality has a weaker effect on happiness or is no more correlated with happiness after controlling for wealth. Alternatively, Berg & Veenhoven (2010) results turned from a negative correlation between life satisfaction and income inequality to more positive if GDP is controlled for. Or, Veenhoven (2005) also observed a positive turn if the country's wealth is controlled for. Additionally, the importance of the national or region wealth variable also supported studies by Ng & Diener (2019) and Haller & Hadler (2006). Alternatively, Du *et al.* (2019) discovered significant evidence of the negative association between inequality and happiness while also controlling for variables such as age, gender, education, income, ethnicity, marital and residence status emphasizing the importance of the financial wealth variable.

- **Inequality reduction** When the inequality reduction variable is included in the regression, it yields a negative estimated effect with the highest possible PIP value of 1.000, indicating that this variable is decisive for estimating income inequality effect on subjective well-being. In particular, accounting for inequality reduction results in -0.124 smaller coefficients on average. The inequality reduction control variable symbolizes the effect of government taxes and transfers on the income inequality (Schwarze & Härpfer 2007). And, it can influence the relationship between income inequality and happiness, since the higher the inequality reduction, the more generous the welfare services provided by the state are likely to be (Hajdu & Hajdu 2014).As mentioned by Cheung (2018), income redistribution at the governmental level by tax and welfare policies represents an incentive to reduce income inequality and its detrimental effects, such as lowering citizen's subjective well-being.

Microeconomic effects

Aside from macroeconomics characteristics, other possibly important factors causing variation in estimates of the income inequality impact on subjective well-being are individual characteristics. Altogether, we have controlled for 15 individual characteristics in our meta-regression model from which only six are significant according to the Bayesian model averaging results. The variables trust in people, employment, health, and religion achieved the highest PIP possible. The variable social mobility shows a weak significance, and the number of children variable a strong significance. Although some researchers from our primary studies account for the number of children variable in the regression of income inequality on happiness, the variable is not generally considered of great importance. Even though Haller & Hadler (2006) suggest that the people with children have higher life satisfaction and therefore considers it important to control for it in the regression estimating the impact of income inequality on happiness.

The results for microeconomic effects are consistent across all three techniques only for four variables out of 15, namely: perceived trust in people, health, employment, and religious status. Additionally, the Frequentist Model Averaging approach finds significant also individual's residential and marital status variable. Thus because of insignificant results for the social mobility variable from the Frequentist Model Averaging analysis, we cannot generally conclude that the mobility variable is significant for the relationship between income inequality and happiness.

As a result, our findings are not in line with the strand of literature supporting the tunnel effect theory by Hirschman & Rothschild (1973) and the significance of perceived social mobility in the relationship between income inequality and happiness. Such as Senik (2004) who confirmed the tunnel effect in the context of the very volatile environment in Russia. Alternatively, Graafland & Lous (2018) found out that the impact of actual income inequality on life satisfaction depends on perceived mobility. Similarly, Yan & Wen (2020) confirmed the tunnel effect theory for the rural residents in China. Wang *et al.* (2015) also find evidence of the tunnel effect in China using the Chinese General Social Survey data. Ravazzini & Chávez-Juárez (2018) found that the mobility is essential while explaining the income inequality-happiness link for all socio-economic groups in Europe. The importance of perceived mobility on the impact of income inequality on subjective well-being confirmed several other papers such as Alesina *et al.* (2004); Fischer (2009) or Schalembier (2019).

- **Trust** The inclusion of the variable concerning the trust in people into the regression model appears to have a decisive factor, with the highest PIP value of 1.000. The results suggest a positive impact, with the posterior mean equal to 0.067. Our findings align with the literature since many researchers have found that the perceived trust in people variable, also called social capital, is the very important for the relationship between income inequality and subjective well-being, such as Engelbrecht (2009); Zhang & Churchill (2020); Huang (2019); Verme (2011). Also, Delhey & Dragolov (2014) found out that the reason Europeans are income inequality-averse is distrust and status anxiety. More precisely, that trust in people is the most important factor for the relationship between income inequality and happiness among wealthy societies. Similarly, according to results by Oishi *et al.* (2011) the negative link between income inequality and happiness is explained by perceived fairness and general trust. Moreover, Oishi *et al.* (2011) also mentions that relative and absolute income do not affect the inequality-happiness link, which is also in line with our research. Also, according to Mikucka *et al.* (2017), policymakers should promote economic growth, protect and promote social trust, and reduce income inequality to achieve long-term changes in people's subjective well-being around the world. To conclude, the social trust is perceived as one of the most important factors affecting income inequality impact on subjective well-being in the respective literature. Our meta-analysis supports this significant strand of literature, thus also supports the status-anxiety or the spirit level theory.

- **Religion** The inclusion of the religion variable into the regression has a PIP value of almost 1.000, signifying that this variable is decisive for estimation income inequality effect on subjective well-being, with the posterior mean equal to -0.063. Not many studies stress the importance of controlling for religion variable in their models estimating the income inequality effect on subjective well-being. Nevertheless, researchers Joshanloo & Weijers (2016) in their two studies, multi-level analyses on 85 nations worldwide and the 27 European nations, found evidence supporting that religiosity mitigates the negative effect of income inequality on subjective well-being. As mentioned by Haller & Hadler (2006), there is a logical explanation why the fact that the individual is religious could influence the inequality-happiness relationship. Since most religions are based on the idea that men's destiny depends on God, their happiness might not be significantly affected since religious people stand better adverse events and experiences. Our results support the importance of the variable for the model estimating the relationship between income inequality and happiness and suggest that more studies should consider including this variable into their models.

- **Health status** The inclusion of the health variable into the regression model is likely to produce on average 0.034 higher effect than if not included. The PIP implies decisive significance with the value of 1.000. Our results are in line with previous research since, according to Haller & Hadler (2006) or Helliwell & Huang (2008), subjective health represents a significant variable for estimating the income inequality effects on happiness. Similarly, Muffels *et al.* (2012) found a negative relationship between subjective well-being and income inequality, and concludes that bad health, employment status, divorce, or separation are the most significant controlling variables. Additionally, Wang *et al.* (2015) found that health and education are the two individual characteristics that have the greatest impact on the happiness-income inequality relationship.

- **Employment status** The inclusion of the employment status variable has an average negative effect of -0.027 on the relationship between subjective-well being and income inequality. The PIP implies a decisive significance value of 1.000. Our results are in line with previous research. Since according to research by Oshio & Kobayashi (2010) and Oshio & Kobayashi (2011) among all individual and regional characteristics, employment status is one of the most important to control for in estimating the relationship between income inequality and perceived happiness. Additionally, the importance of the employment status control variable also supports Schneider (2019).

Publication characteristics

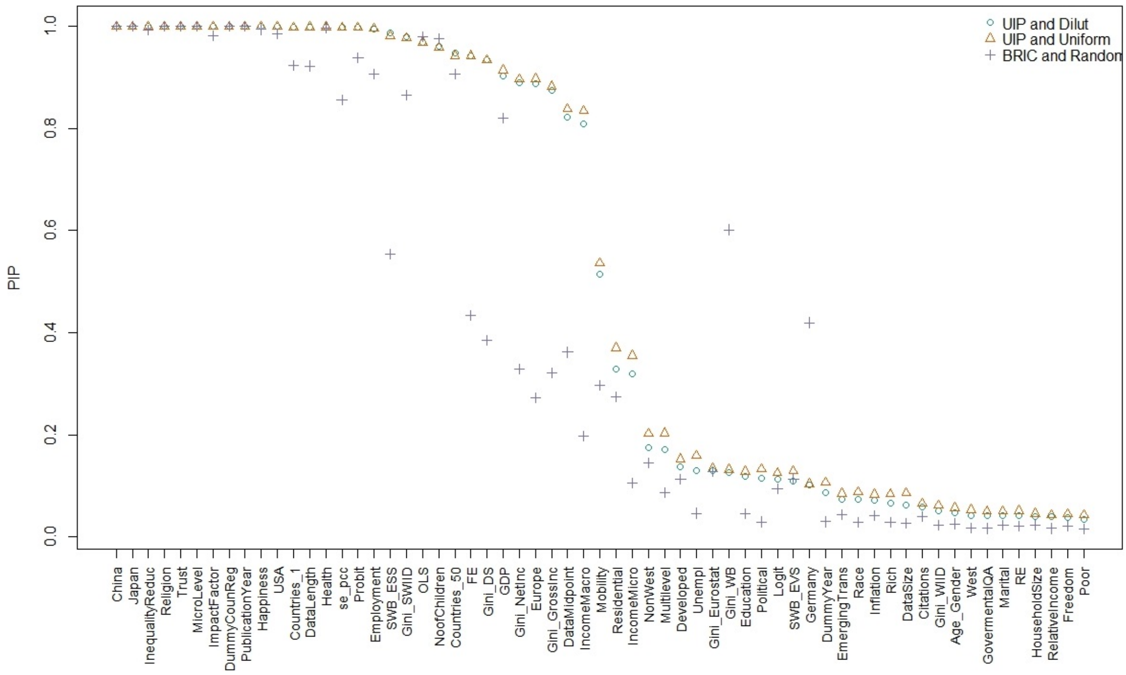
Publication characteristics variables are also essential since two out of three are systematically associated with the magnitude of the income inequality effect on subjective well-being. Both publication year and impact factor variables obtain decisively high posterior inclusion probability, as opposed to a number of citations variable. The results for publication characteristics are robust across all three methods we apply (the Bayesian model averaging, the Frequentist model averaging, and the OLS-based frequentist check).

- **Publication Year** The inclusion of variables indicating the publication year, calculated as the logarithm of the year with respect to the earliest year used in the sample, resulted in a decisive PIP of 1.000 and the posterior mean equal to -0.178, indicating that the most recent studies have consistently lower findings. Possibly, it is because they might reflect the changes in the methodological and estimation techniques. Our findings also support the fact that the relationship between happiness and income inequality is time-sensitive. Since all of the time-related control variables, such as publication year, data length, and data midpoint, we found important for the relationship between income inequality and SWB.

- **Impact factor** The inclusion of the impact factor on average suggests the production of the estimate of income inequality effect on happiness 0.142 higher. The PIP has a decisive value of almost 1.000, providing significant evidence suggesting a strong association between the estimated results and the journal's quality in which the study was issued. Since also journal's quality is likely to reflect the quality of the particular study.

In our meta-analysis, aside from our baseline Bayesian Model Averaging (BMA), Frequentist model averaging (FMA), and frequentist check, we also apply alternative priors to dilut, the results of various priors could be seen comparably in Figure 5.2, as well in Appendix C together with diagnostics of BMA.

Figure 5.2: Sensitivity of Bayesian Model Averaging to various priors



Notes: UIP and Uniform = priors according to Eicher *et al.* (2011) UIP and Dilution = priors according to Eicher *et al.* (2011) and George (2010), respectively. BRIC and Random = the benchmark g-prior by Fernandez *et al.* (2001) for parameters with the beta-binomial model prior for the model space, thanks to which each model size obtains equal prior probability. UIP = unit information prior, PIP = posterior inclusion probability.

In general, we can conclude that it does depend on variables specifications of both income inequality and subjective well-being (SWB) based on our findings. Although most researchers who examine the impact of income inequality on SWB claim that life satisfaction and happiness measures could be taken simultaneously. According to our results, the impact of income inequality on happiness and life satisfaction might differ. More precisely, our findings show that using happiness as a measure of SWB is linked with more positive income inequality effects, compared to using life satisfaction. Additionally, the estimates using income inequality measure based on net and gross income, instead of other income groups like expenditure and consumption, are associated with more negative results. Among the main sources of heterogeneity belongs also individual and country's or region's characteristics, based on both model averaging techniques and frequentist check. Namely, controlling for the trust in people, individual's health status or country's wealth, is associated with higher income inequality effect on SWB. Contrarily, controlling for employment and religious status is connected to a lower effect on reporting estimate. As Zhang & Churchill (2020) claim, the trust in people is one of the few channels of influence that gathered more attention in the relevant literature than others. Thus, our results support this strand of literature, since based on our findings the trust in people is very important for the relationship, also supporting the social anxiety theory or the spirit level theory by Pickett & Wilkinson (2010). On the other hand, according to our results, perceived social mobility is not that important for the relationship between income inequality and SWB, not supporting the tunnel theory by Hirschman & Rothschild (1973).

Additionally, a large portion of the variation in the income inequality effect on subjective well-being can also be explained by data characteristics, namely by data midpoint, data length, micro-level. Our findings shows a a slight upward trend in the observed impact of income inequality on subjective well-being. Next, if researchers use the individual-level subjective well-being and the country's or region's income inequality also as an individual variable, the income inequality effect on happiness tends to be lower, according to our results. Also, controlling for dummy variables for countries and regions produces a decisive factor and probably lower effect estimates. Moreover, estimation characteristics also matter. If the primary studies uses the OLS estimation technique, the income inequality effect on SWB tends to be significantly higher. Conversely, if ordered probit and fixed effect are used, the effect is likely to be lower. More importantly, our findings also show that it also depends on the geographic region for which the income inequality effect on happiness was estimated. Namely, the effect of income inequality on subjective well-being is likely to be systematically more negative for the United States, China, and Europe. Our findings also provide significant evidence suggesting a strong association between the estimated results and publication characteristics.

Chapter 6

Conclusion

This thesis synthesized 868 estimates of the effect of income inequality on subjective well-being from 53 studies. To the best of our knowledge, it is the first meta-analysis on the relationship between income inequality and subjective well-being that includes publication bias analysis or a systematic analysis of literature heterogeneity. The relationship between subjective well-being and income inequality is essential for welfare policy decisions. It is startling that despite the ambiguity of the literature regarding the inequality-happiness link, there have been only a few reviews and one meta-analysis conducted in this area. The prior reviews and first meta-analysis (Ferrer-i Carbonell & Ramos 2014; Schneider 2016; Ngamaba *et al.* 2018) testify to a large heterogeneity present in the literature concerning the relationship between income inequality and subjective well-being. They conclude that there could be certain aspects of data and measurement choice systematically driving the resulting reported income inequality effect on subjective well-being and calls for further research. Nevertheless, no one has investigate the drivers of the relationship between income inequality and subjective well-being systematically, as far as we are concerned.

Thus, the main contribution of our thesis is the complex comprehensive analysis of the heterogeneity of the relationship between income inequality and subjective well-being. Firstly, we enlarge the data set of prior meta-analysis Ngamaba *et al.*

(2018) almost forty times, from 24 observations (zero-order correlations) to 868 observations, and more than double the number of primary studies. We transformed the estimates into partial correlation coefficients (PCC) since the estimates of income inequality effect on happiness were not directly comparable mainly because of the varying scale of the subjective well-being measure. Additionally, although prior narrative reviews exist (Ferrer-i Carbonell & Ramos 2014; Schneider 2016), they review up to 25 studies. So, our thesis is also the first narrative review on the relation between income inequality and subjective well-being, including more than 25 studies, to the best of our knowledge. We also contributed by reviewing both happiness and income inequality topics separately, and the concepts on which their complex relationship is based. Our literature review of 53 primary studies also includes the most recent researches. Namely, we were able to include 14 studies published after 2018, which suggest how this topic is increasing in popularity, thus our thesis may provide support for further future research. Nevertheless, most importantly, we contributed by testing the respective literature for the presence of publication bias and addressing the heterogeneity complexly with multivariate analysis.

To avoid potentially biased results of the income inequality effect on happiness, we have also decided to analyze the presence of publication bias in the respective literature, since no one before has analyzed it. Firstly, we examined at publication bias using the funnel graph, a graphical analyzing method that shows a slight preference for reporting negative income inequality effects on subjective well-being. Secondly, we performed less subjective, more formal state-of-the-art recent tests for detecting publication bias. We showed that publication bias exist in the literature concerning the relationship between subjective well-being and income inequality but is created by selecting individual studies. If we assign equal weight to all of our 53 studies, the presence of publication bias is not statistically significant in the literature. Furthermore, according to our results, the effect of income inequality on subjective well-being corrected for the publication bias is negative but very small, close to zero.

Besides the publication bias, to determine the key factors driving the income inequality effect on subjective well-being and causing the heterogeneity, we examined the majority of the characteristics of the primary studies. Next to estimates, we managed to collect 78 additional explanatory variables from all of our 53 primary studies. To address the uncertainty's model specification, we applied the Bayesian model averaging (BMA) and the frequentist check based on OLS. In addition, we used Frequentist Model Averaging as a robustness check for our results. The findings of all three techniques are very similar. Even after accounting for 62 features of the study design, publication bias survives in the unweighted sample. Several characteristics of the study design, according to our findings, explain why the estimates in our 53 primary studies vary systematically.

We found out that both income inequality and subjective well-being specifications systematically drive the estimates. Researchers who prefer using happiness as a subjective well-being measure tend to obtain decisively larger estimates than ones using life satisfaction as a subjective well-being measure. This finding contradicts many studies on the relationship between income inequality and subjective well-being, which claim that there are no differences between life satisfaction and happiness measures. Moreover, when the Gini coefficient based on gross or net income is used as a measure for income inequality, then the income inequality effect on happiness tends to be more negative, based on our findings. Also, when researchers include into their regressions, variables about perceived trust in people, individual's health status or country's wealth, the reported effect of income inequality on subjective well-being is likely to be higher. Contrarily, if an individual's religion or employment status is controlled for, then the reported estimate is likely to be lower. The decisive importance of the trust variable for the relationship between income inequality supports the social anxiety theory, or the spirit level theory by Pickett & Wilkinson (2010).

Additionally, based on our findings, a substantial portion of the variation in the income inequality effect on subjective well-being can also be explained by data characteristics, more precisely by data midpoint, data length, micro-level. Also, controlling for dummy variables for various countries and regions is likely to produce significantly lower effect estimates. Most importantly, our findings also reveal significant geographical and country variations, implying that income inequality has a more negative effect on happiness in the United States, Europe, and China. Moreover, based on our findings also publication characteristics have a decisive effect on the relationship between income inequality and subjective well-being, namely the journal recursive impact factor and publication year.

Although our meta-analysis does not provide the government with policy prescriptions for this very complex relationship between income inequality and subjective well-being, it does provide very important and valuable recommendations on which direction future policy-related research should be conducted. Since the relationship between income inequality and subjective well-being is of general concern and crucial for governments and their decisions regarding various welfare policies. More precisely, it could help the policy-makers who stand behind the income redistribution process from the rich to the poor. We hope that empirical and narrative parts of our thesis will help future research concerning the income inequality effect on subjective well-being. Since further research is needed in order to provide more evidence on this complex and ambiguous relationship. So that the academic literature regarding the relationship between income inequality and subjective well-being will be closer to a consensus. Our research could also, for example, serve as an incentive for future research to consider a possible difference between happiness and life satisfaction measures, contrarily to prior research. In general, future research could focus on several factors that we have shown to drive the relationship systematically to shed new light on the relationship.

Few qualifications of our results are in order. First, we have a highly heterogeneous sample of the definition of the relationship. Not to mix apples with oranges, we tackle the problem by recalculating the effects to a common metric, the partial correlation coefficients (Doucouliagos *et al.* 2011). Even though it cannot be considered an ideal solution, the partial correlation coefficients keep the ordinality of the effects. Thus if it is close to zero, we can deduce that the effect is very small. Second, simple treatment of publication bias that relies on the relationship between the estimates and their standard errors could not be an ideal solution since the standard error itself is an estimate, and the researchers have some degree of freedom influencing its magnitude. To tackle this issue, we use brand new techniques from the psychology research, p-uniform* (van Aert & van Assen 2020), which does not rely on this relationship. Third, it is unlikely that published estimates from the same study are independent. To address this issue, we cluster standard errors at the study level.

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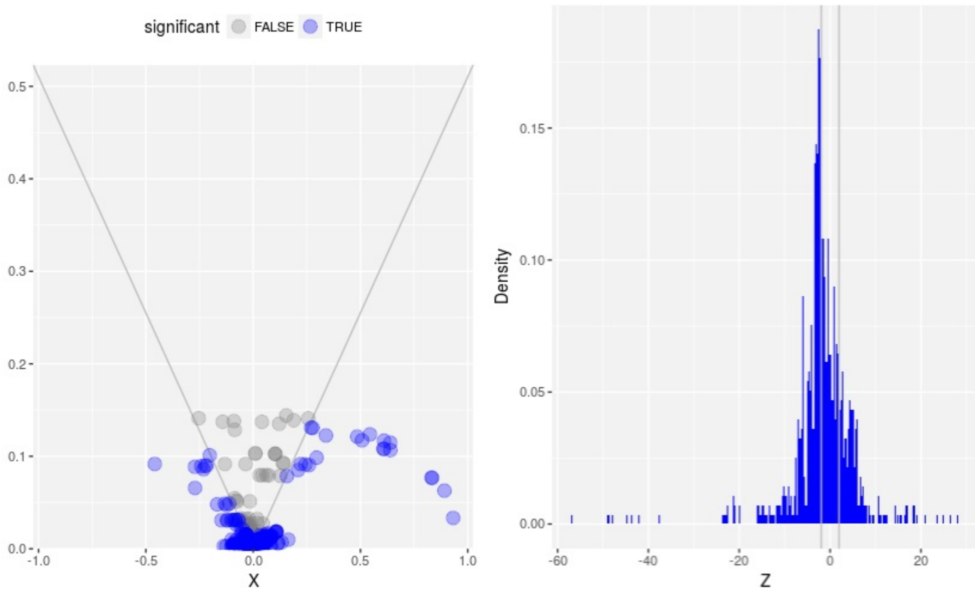
Appendix A

Andrews and Kasy's Method for Addressing Selective Reporting

Figure A.1: A graphical illustration of estimator from Andrews & Kasy (2019)



Notes: Graphs illustrating the basis of the Selection model from Andrews & Kasy (2019), where the solid lines represents t-statistic equal to |1.96|. The left graph plots the PCC at x-axis and their standard errors in y-axis, the gray points represents insignificant estimates and the darker ones represent significant ones. Since some insignificant estimates can be observed in the graph, the publication selection based on significance cannot be taken as absolute.

Table A.1: Results of estimator of Andrews & Kasy (2019)

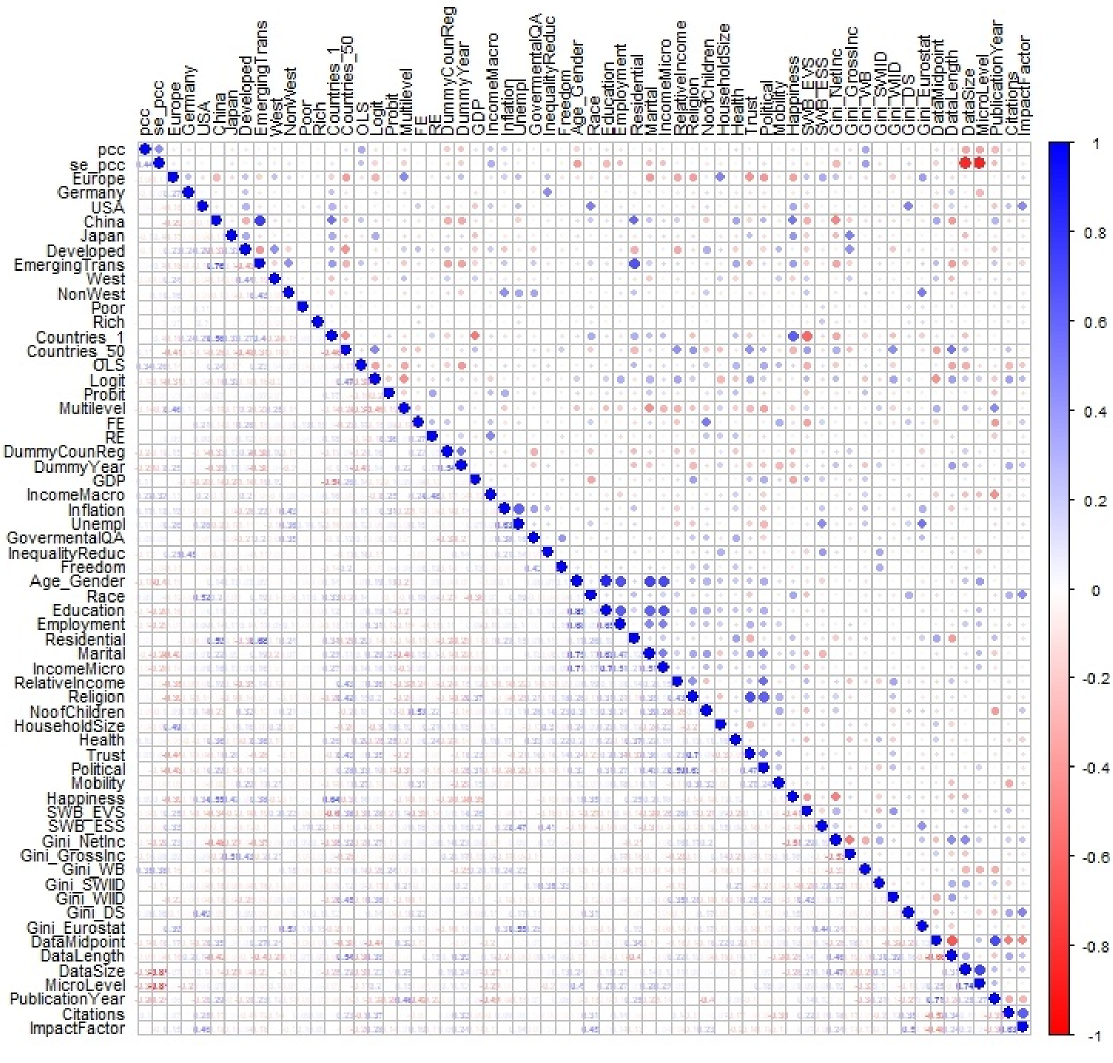
	$\bar{\theta}$	$\bar{\tau}$	df	$(-\infty; -1.96]$	$(-1.96, 0]$	$(0, 1.96]$
Estimate	-0,008	0.010	1.950	0.816	0.313	0.365
Standard error	0.001	0.001	0.113	0.147	0.050	0.053

Notes: In the table symbol $\bar{\theta}$ represents the bias-corrected mean effect, $\bar{\tau}$ represents a scale parameter, df is shortage of degrees of freedom.

Appendix B

Correlation matrix

Figure B.1: Correlation matrix of the 62 explanatory variables included in the heterogeneity analysis



Appendix C

BMA diagnostics and Robustness Checks

Figure C.1: Posterior and Prior Model Probabilities in BMA

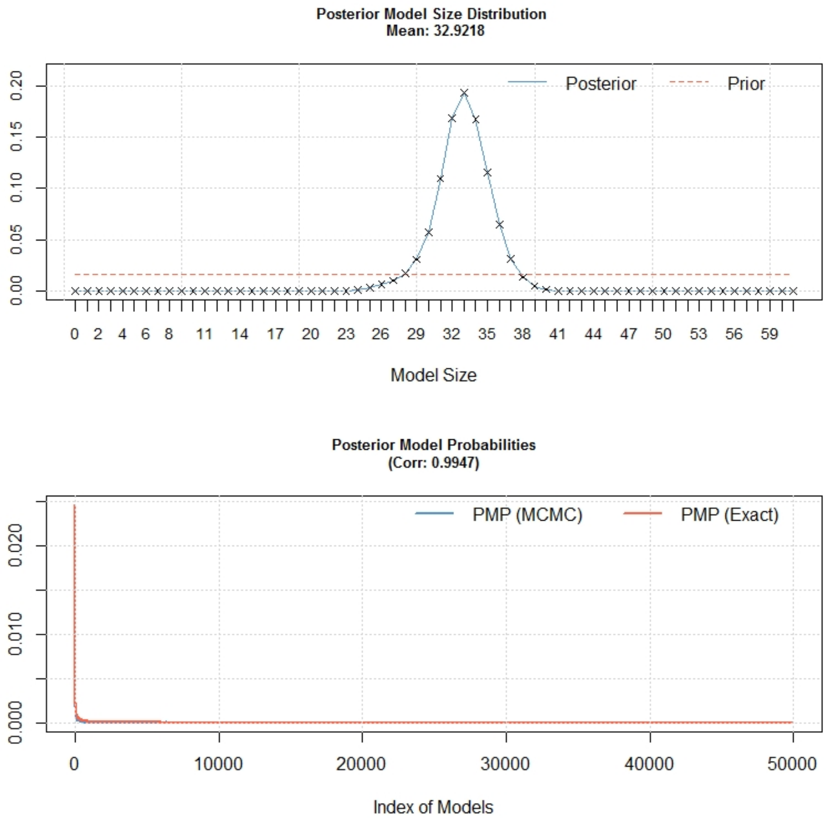
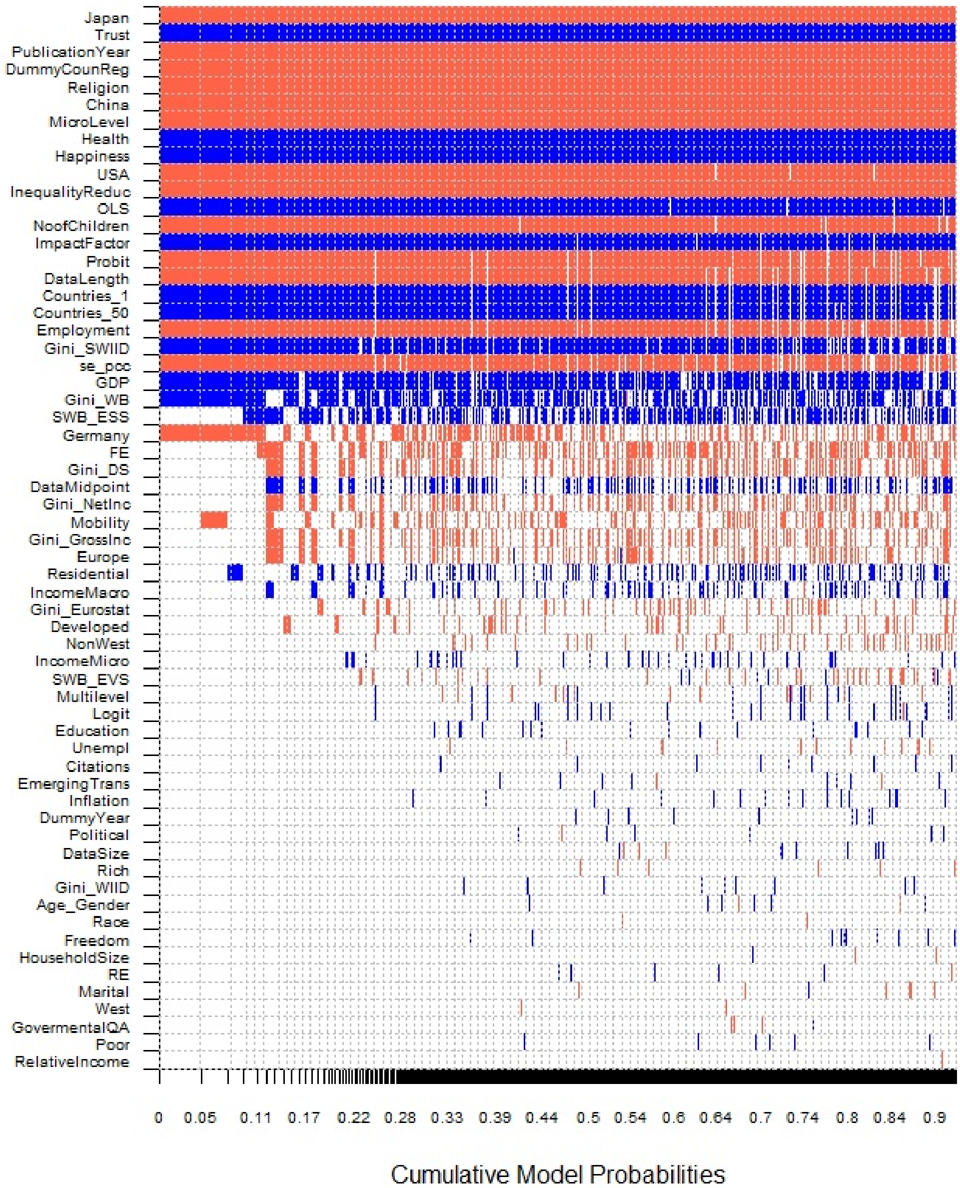


Figure C.2: Model inclusion in Bayesian Model Averaging - g = "BRIC", mprior = "random"



Notes: The figure depicts the results of BMA analysis executed for analyzing the effect of income inequality on happiness with winsorized data at 1% level on both distributions' side. The vertical axis = depicting explanatory variables sorted from the one with highest posterior inclusion probability at the top, to lowest at the bottom. The horizontal axis = depicting the cumulative posterior model probabilities. The blue (darker in greyscale) coloured cells = showing the estimated effect of a relative variable is positive. The red (lighter in greyscale) coloured cells = showing the estimated effect of a relative variable is negative. White color - showing that the variable is not included in the model.

Figure C.3: Posterior and Prior Model Probabilities in Bayesian Model Averaging - g = "BRIC", mprior = "random"