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PhD Coordinator: Prof. Simone D'Alessandro

PhD Thesis

Essays on Social Capital and Wellbeing

Supervisor:
Prof. Stefano Bartolini

Candidate:
Giulia Slater

Co-Supervisor:
Dr. Francesco Sarracino

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Extended Abstract

This thesis is comprised of four empirical papers. The first paper (coauthored with Stefano Bartolini, Marcin Piekałkiewicz and Francesco Sarracino), entitled **"Social capital reduces the impact of social comparisons on subjective wellbeing: Evidence from international datasets"**, uses EU-SILC, ESS and EVS-WVS cross-sectional data, and German SOEP panel data to show that social capital changes the association between income and subjective wellbeing, and the one between social comparisons and subjective wellbeing. The paper also tests the hypothesis that at the macro-level, in countries that are rich in social capital, the differences in subjective wellbeing between income groups are small, which is a consequence of the relatively smaller impact that income and social comparisons exert on wellbeing. The second paper, entitled **"The wellbeing effects of social capital in times of a health crisis: the case of the Covid-19 pandemic"**, uses monthly UKHLS data to assess whether social capital influenced the way people fared throughout the first year of the Covid-19 pandemic. The paper provides a theoretical intuition of the mechanisms via which social capital affects wellbeing and mental health in times of a health crisis, and provides evidence that social capital is beneficial to subjective wellbeing as it allows resilience. The third paper, entitled **"Loneliness increases the probability of worse mental distress development during Covid-19"** uses latent class analysis, a non-parametric model, to explore the heterogeneity in mental distress development in the UK during the Covid-19 pandemic. It subsequently relates individuals' loneliness, a measure of lack of social capital, to the probability of being on either class of distress development. Results suggest that the probability of being on a trajectory of continuously high distress was significantly higher for people who are often or sometimes lonely, compared to non-lonely people. The last paper (coauthored with Stefano Bartolini and Francesco Sarracino), entitled **"Do epidemics impose a trade-off between freedom and health? Evidence from Europe during Covid-19"** analyses whether the extent to which governments imposed stringent containment policies in face of the pandemic was determined by the trust levels of citizens. Additionally it tests whether less stringent containment policies came at the expense of health. The findings suggest the trade-off between freedom and health depends on the levels of trust, in particular that the trade-off reduces with higher levels of trust. The conclusions of these papers all point to the need of promoting social capital as a critical element for people's and societal wellbeing.

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Chapter 1

Introduction

1.1 Introduction and scope of the dissertation

This dissertation contains four essays on social capital, with a particular focus on its wellbeing consequences. The chapters are self-contained and can be read independently, but all contribute to the understanding of how social capital operates for subjective wellbeing, as well as for public health and governance. The analysis of the relationship between social capital and wellbeing is not entirely new to the literature; however, I bring novel evidence on social capital as a facilitator of subjective wellbeing and public health outcomes both directly and indirectly, in two different settings. First, in the second chapter of this thesis, I analyse the income-wellbeing and social comparisons-wellbeing nexus, and the moderating role that social capital plays in these relationships. The findings suggest that people with high social capital attach less importance to their income and to social comparisons. This reflects, at the macro-level, on the wellbeing distribution between people with different income levels: in countries with higher social capital, the wellbeing differences between rich and poor people are lower than elsewhere. Second, in the last three chapters, I analyse the relationship between the Covid-19 pandemic, social capital and wellbeing. The pandemic brought societies to their knees for two reasons: it imposed strong limitations on people's relational freedom, and these, in turn, had enormous costs on subjective wellbeing, as well as on the economy. I find that social capital played a key role in mitigating the negative consequences of the pandemic on both issues. In particular, I find that higher social capital allowed for less stringent containment policies, and for a higher subjective wellbeing throughout the pandemic period. This is striking because lockdowns and containment policies entailed a deprivation of social capital, at least in the form of social interpersonal relations, that one may expect to have closed or inverted the subjective wellbeing gap usually in favour of high social capital people.

In the literature, social capital has been shown to have a direct positive effect on subjective wellbeing (see, among others, Bartolini et al. (2013); Helliwell (2006); Helliwell and Putnam (2004)). It has also been found to moderate the relationship between negative events and wellbeing (as an example, see Helliwell et al. (2014)) and to have a sheltering effect against adversities and negative correlates of wellbeing, via the provision of an informal safety net and psychological support (Lindström and Giordano, 2016; Sarracino and Piekałkiewicz, 2021; Aldrich, 2011; Adeola and Picou, 2012). As mentioned above, one of the central questions that I tackle in this thesis is whether these findings also held during the Covid-19 crisis. Indeed, it could be expected that the sheltering effect of social capital did not hold, as pandemic containment policies imposed limitations to individuals' relational freedom, with negative consequences for their subjective wellbeing. My results show social capital allowed for higher wellbeing and wellbeing resilience even during social isolation periods, and I discuss that the resilience effect derives from the values that social capital leaves within people, even when they are unable to socially meet. Moreover, I find that trust, an essential component of social capital, eased the trade-off between freedom and health that is imposed by epidemics. Social capital played an essential role in managing the Covid-19 crisis because it was critical both for reducing the limitations to relational freedom, and to decrease the negative wellbeing consequences of such limitations. The conclusion is that social capital is a key element to reduce the impact of epidemics on societies, from an individuals' subjective wellbeing perspective as well as from a public health perspective. This is a fundamental consideration given the increasing likelihood of epidemics in the future (Smith et al., 2014; Baker et al., 2022).

In brief, this thesis covers three fundamental questions for contemporary societies whose aim is targeting individual and societal wellbeing: firstly, how to reduce the negative effects of social comparisons for wellbeing; secondly, how to mitigate the need to impose limitations to interpersonal relational freedom in face of infectious diseases; and third, how to reduce the negative wellbeing impact of the deprivation of social capital stemming from the limitations to relational freedom. The answer to these three questions is promoting social capital.

In the remainder of this chapter, I provide a short introductory review of the literature on wellbeing and social capital and highlight the contribution of my findings within this literature; I additionally discuss that studying and understating wellbeing is valuable to societies and economies; and finally, I detail the contents of the next chapters.

1.2 Introcuctory Literature Review

People's wellbeing is among the most debated topics in public policy and in social sciences research[1]. Economists and social scientists have always been concerned with the pursuit of humans' wellbeing, but in lacking the appropriate measures to identify it, they typically resorted to conducting quantitative analyses on *objective* measures of wellbeing that do not depend on individuals' assessments and are independently verifiable by third parties. Among these are income and gross domestic product (GDP), material resources (food or housing) and social attributes (health and education, among others). However this approach, especially the study of income and GDP, neglects important parts of human wellbeing (Graham et al., 2005). For instance, it does not consider non-market goods that people enjoy in their daily lives, such as the quality of their relationships and of the environment they live in; the emotional support, material and behavioral assistance; and information they receive from others in their social networks (Jackson et al., 2017; Thoits, 2011; Umberson and Karas Montez, 2010).
Recent developments of the social sciences allowed to further the understanding and the measurement of wellbeing by taking into account individuals' evaluations of their lives as a whole, as well as their daily feelings and conditions. These are *subjective* measures of wellbeing – such as life satisfaction (a cognitive evaluation), happiness (a positive emotional state) and unhappiness (a negative emotional state) – which are internally determined based on one's circumstances and standards, and regard people's own evaluations of their lives (Diener and Suh, 1997; Diener et al., 1985) and their feelings and experiences (Krueger and Stone, 2014). The developments in the study of *subjective* wellbeing by now bring enough evidence of the reliability and validity of its measurements to correctly represent individuals' wellbeing, which allowed for a huge number of works being published in the field of happiness research (Layard and Ward, 2020), and to promote subjective wellbeing as policy target (Layard, 2022; Frijters et al., 2020; Clark et al., 2019; Layard, 2011), or to complement objective wellbeing indicators like GDP in policy making (OECD, 2013; Stone and Mackie, 2013; Krueger and Stone, 2014; Diener et al., 2009b).

The analysis and measurement of subjective wellbeing has a long-standing tradition that is grounded in social psychology. This literature started developing in the 1970s and flourished after 2000 when subjective wellbeing increasingly entered the research agendas of other social sciences, including economics (Bruni and Porta, 2005).
Subjective wellbeing usually refers to individuals' *evaluations* of their own wellbeing, which is observed through answers to survey questions such as the following: "*All things considered, how satisfied are you with your life as a whole these days?*" (Van Praag et al., 2003). In this way, people are able to evaluate what is important in their life and implicitly assign relative weights to each aspect. For many years there had been little quantitative informa-

[1] See for instance Layard (2022, 2017); Bartolini and Bilancini (2010); Helliwell (2006); Bruni and Stanca (2008); Kahneman et al. (1999) and the references therein.

tion on this subject. However, since the 70s a whole new science of wellbeing has developed (Clark et al., 2019; Kahneman et al., 1999). In particular, researchers have validated subjective wellbeing measures over objective health measures (such as heart rate, blood pressure, duration of Duchenne smile and neurogical tests of brain activity; see, among others (Blanchflower and Oswald, 2008; van Reekum et al., 2007)), they have shown that they are consistent with evaluations about the respondent's wellbeing provided by friends, relatives or clinical experts (Schneider and Schimmack, 2009; Kahneman and Krueger, 2006; Layard, 2011) and they have proven their correlation with other proxies of subjective wellbeing, such as happiness and positive affect (Schwarz and Strack, 1999; Schimmack et al., 2009). Indeed other than evaluative wellbeing (i.e. life satisfaction), other dimensions of subjective wellbeing that are typically studied gauge the "experienced wellbeing" of people, such as happiness[2], suffering and mental health, which measure peoples' moment-to-moment and day-to-day feelings of pleasure, contentment, pain, and other emotions (Stone and Mackie, 2013; Pavot and Diener, 1993; Van Praag et al., 2003). Subjective wellbeing measures are regarded as reliable sources of information on people's feelings and there is wide agreement that they may be used to assess people's actual wellbeing and its determinants.

Economists' interest in the study of subjective wellbeing data derived from the fact that they could use them to measure welfare or utility. In fact, using subjective wellbeing as a measure of utility allows to estimate regressions that identify economic and non-economic components of wellbeing. Among the most commonly studied economic determinants of subjective wellbeing are income and GDP. Happiness data have been used to study the role of income for people's subjective wellbeing. On the one hand, results generally suggest positive but diminishing returns to income for wellbeing[3] (Dolan et al., 2008). Essentially, research finds that at any point in time, within countries, wealthier people report on average higher subjective wellbeing than poorer ones, but with decreasing marginal returns. On the other hand however, Easterlin (1974), in his influential contribution on the relationship between economic growth and subjective wellbeing, reported that over time there is almost no relationship between increases in per capita income and in average wellbeing levels.

The findings that in a cross-section higher income correlates to a higher wellbeing and that in the long run economic growth and wellbeing trends are uncorrelated is now commonly referred to as "Easterlin Paradox", and it has been subsequently corroborated in many settings and across countries (Mikucka et al., 2017; Becchetti et al., 2011; Easterlin et al., 2010; Easterlin and Angelescu, 2009; Bruni and Stanca, 2008). Two possible explanations to the paradox were originally proposed by Easterlin (1974) which hinge on two widely explored theories on human behaviors (Frederick and Loewenstein, 1999; Diener et al., 2009a): i) hedonic adaptation, that is the tendency people have of getting used to

[2]The typical question being asked to assess people's happiness is: "*All things considered, how satisfied are you with your life as a whole these days*?"

[3]Clark et al. (2008) provide a comprehensive review of the relationship between income and subjective wellbeing.

changes in their circumstances, such as in their incomes, which only have a transitory effect on wellbeing which remains at its baseline level; and ii) social comparisons, a mechanism for which people compare their income, achievements and status with those of a *reference group*, that is a group of people with whom individuals' compare themselves. Since then, other researchers studied the importance of relative income and status and concluded that wellbeing is strongly affected by them (see, among others, Ferrer-i Carbonell (2005)).

While peoples' wellbeing depends on income, both theirs and that of others, there are many other factors that contribute to how people evaluate and feel about their lives, such as their health, their education level and their employment status (Clark et al., 2019; Dolan et al., 2008). Extensive research however suggests that among the most important correlates of wellbeing is social capital.

Social capital is a much debated topic on which many definitions and descriptions have been proposed. In general, social capital entails the shared norms and values that are available within a society, as well as the emotional support, and material or behavioral assistance between people. This concept has been used to describe several interrelated and overlapping phenomena that are associated with individuals' relationships to resources and people around them. Many researchers follow Putnam's original conceptualisation of social capital as the interpersonal relations which provide benefits that create value for the people who are connected, and for the bystanders as well (Putnam et al., 2001, 2000; Putnam, 1995). Social capital can then be thought of the social networks and norms of reciprocity and trustworthiness arising from interpersonal relations that create value for individuals and communities, and is most commonly defined as "the networks, together with the shared norms, values and understandings that facilitate cooperation within and among groups" (OECD, 2001).

In recent years, the scientific debate has paid considerable attention to the causes and consequences of social capital, which can be thought of as a catalyst for many socially relevant outcomes, such as economic growth (Bowles and Gintis, 2002; Knack and Keefer, 1997; Arrow, 1972); development, democracy and the quality of democratic infrastructure and institutions (Putnam et al., 1992); economic connectedness and mobility (Chetty et al., 2022a,b) as well as for mental and physical health (Ehsan et al., 2019; Umberson and Karas Montez, 2010; Thoits, 2011; Kawachi et al., 2008; Berkman et al., 2000); longevity (Jetten et al., 2010; Cohen and Wills, 1985); and public health (Reames et al., 2021; Chuang et al., 2015; Rönnerstrand, 2014; Lynch et al., 2000). Most recently, since the start of the global health crisis of the Coronavirus pandemic in 2020, the role of social capital has been acknowledged for the successful containment of the pandemic (Bowles and Carlin, 2020); for guaranteeing lower economic costs and lower mortality rates (Abi-Rached and Diwan, 2021); to explain variations in infection rates between regions (Makridis and Wu, 2021); and to analyze citizens' compliance with social distancing rules (Petherick et al., 2021; Bargain and Aminjonov, 2020) and their mobility patterns (Borgonovi and Andrieu, 2020; Durante et al., 2020). While an extensive review of the measurement and consequences of social capital is outside the scope of this chapter, in the following I will focus on its health and subjective wellbeing effects, as they are the main focus of this dissertation.

Following Putnam's work (Putnam et al., 2000, 1992) the most common measure of social capital used in the wellbeing literature is sociability – also referred to as relational goods – which entails the quality and quantity of intrinsic non-market social relationships among individuals (Pena-López et al., 2017; Bartolini and Bilancini, 2010; Becchetti et al., 2008), and is typically proxied by variables such as the frequency of visits with others or frequency of attending social activities; and volunteering, among others. Other frequently used social capital measures are the quality of the social fabric, including the quality of social networks and social norms, cooperativeness and membership in associations or groups, plus several measures of trust or confidence (Bruni et al., 2021; Helliwell et al., 2014; Helliwell, 2007; Helliwell and Putnam, 2004).
Studies from the wellbeing literature generally report a positive correlation between social capital and subjective wellbeing. Research points to the quality of people's experience, that is the quality of the relationships among people, in having a strong positive impact on subjective wellbeing (Tov et al., 2022; Clark et al., 2019; Helliwell et al., 2014; Sarracino, 2012; Bartolini and Bilancini, 2010; Becchetti et al., 2008; Bruni and Stanca, 2008; Helliwell, 2007; Helliwell and Putnam, 2004; Putnam et al., 2000). The same holds true for other measures of social capital, such as membership and participation in groups and associations, and cooperatives (Bruni et al., 2021; Gui and Sugden, 2005) and for the effects of trust (see, among others Bartolini et al. (2013); Helliwell and Wang (2010)) which all positively correlate to various subjective wellbeing measures. In particular sociability and relational goods have been found to positively relate to life satisfaction (Pena-López et al., 2017; Becchetti et al., 2008) and to support physical health (Helliwell and Putnam, 2004). Other proxies of social capital, such as social connections and confidence in institutions, are found to positively and significantly correlate with happiness (Bartolini et al., 2013), and life satisfaction (Sarracino, 2012). Additionally, social capital is found to be a strong predictor of long run growth of subjective wellbeing within and across countries (Sarracino, 2012; Bartolini and Bilancini, 2010).

Similar findings stem from the health and social capital research. Evidence shows that social capital is positively related to health (Hawe and Shiell, 2000; Lomas, 1998). Social networks, acting as buffering factors and support systems, positively affect individuals' mental and physical health from a theoretical standpoint (Berkman et al., 1986; Cohen and Wills, 1985; Seeman, 1996), and empirically as well (see Carpiano (2007); Ichida et al. (2009); Mansyur et al. (2008)).

The links between social capital and subjective wellbeing and health are well defined and hold across countries and over time. Less research has been devoted to explaining what are the pathways via which social capital actually affects wellbeing. Evidence shows that the transmission from social capital to wellbeing is both direct and indirect, for example via health or education (Helliwell and Putnam, 2004) or via economic channels (Helliwell, 2007; Helliwell et al., 2014). It is possible hence that social capital might have a positive effect on wellbeing also indirectly. Moreover, not much research has been devoted to disentangling the mechanisms of propagation from social capital to wellbeing. The following chapters contribute to this literature by tackling these issues. The papers in this thesis contribute to the understanding of how social capital operates for subjective wellbeing, as well as for public health. They answer the timely questions of how to reduce the negative impacts of social comparisons for wellbeing, that of the effects of epidemics for wellbeing, and their containment.

1.3 Why should we study wellbeing?

Despite the importance of subjective wellbeing as a measure of utility and progress (see Stiglitz et al. (2009), and O'Connor (2022) and references therein), it is still largely disregarded in social sciences, particularly in economics[4]. However, governments worldwide are starting to measure the subjective wellbeing of their citizens to evaluate and appraise public policies. Evidence on wellbeing is increasingly entering public policy efforts, as evidenced by the "Wellbeing Budget" in New Zealand and the "Green Book" in the UK, both of which endorse subjective wellbeing reports as sources of evidence.

There are several compelling reasons to study subjective wellbeing and its determinants. Subjective wellbeing is a good measure of utility, it allows to account for non-market goods, and it predicts labour market outcomes. Good mental health and high life satisfaction are linked to socially and economically relevant public outcomes. For example, better physical health (Surtees et al., 2008), greater productivity (Bellet et al., 2019), higher income, reduced absenteeism, and lower drop-out rates (Johar and Truong, 2014) are all associated with high wellbeing. Mental illness, which the WHO deems is becoming a global problem and as such should be considered policy-relevant, also has significant effects on labour market outcomes and public costs (World Health Organization, 2008). The WHO estimated that in the UK, mental illness is the largest cause of disability, with related economic costs estimated at £105.2 billion each year, including direct costs of services, lost productivity at work and reduced quality of life (World Health Organization, 2008;

[4]There is an uptake of the studies done on wellbeing and published in recent years, though it has still not become prevalent in economics studies. There is however an increasing public interest in the understanding of wellbeing. Indeed, in printed books, references to happiness are rising rapidly and have overtaken references to national income or GDP, which are falling (see Barrington-Leigh (2022)).

National Collaborating Centre for Mental Health, 2010). Moreover, common mental health problems, such as anxiety and depression, account for 40% of disability insurance claims in the UK and cost healthcare an extra £10 billion annually (McInnes, 2012), in addition to physical health problems (Layard, 2017). Layard (2017) highlights that the economic costs of mental health in the UK are significant. Moreover, a projection of what the costs to the NHS would be by 2026 shows that they will sharply increase, all else kept equal (Knapp et al., 2011).

From a labour market outcome perspective, Bryan et al. (2020) found that poor mental health leads to a 1.6% point reduction in the probability of employment. Jones et al. (2020) reported that mental health shocks increase the probability of exiting the labour market, reduce wages and hours of work, and have long-term effects on earnings.

It is clear that economists and policymakers must invest in research and resources to prevent and contain the spread of mental illnesses, and measure subjective wellbeing. Assessing what could help in containing increased distress will provide policymakers with evidence to implement prevention and containment measures. In the context of an increasingly complex world, with lower reported wellbeing and life satisfaction, increased mental illnesses, and decreasing levels of social capital, studying wellbeing can help to rethink priorities and reappraise goals for societies. This thesis contributes to this growing body of research by examining the determinants of subjective wellbeing and identifying interventions that promote wellbeing, which include policies for social capital.

1.4 Detailed Summary of the dissertation

In the second chapter of this dissertation, a paper coauthored with Stefano Bartolini, Marcin Piekałkiewicz and Francesco Sarracino, we analyse the role of social capital as a moderator in the income-wellbeing and social comparisons-wellbeing nexus. The reason is that in the subjective wellbeing literature social capital, income and comparisons are considered mutually independent factors that influence wellbeing, with social capital playing a well-established positive role for wellbeing. However, the importance that income and social comparisons exert on wellbeing may depend on social capital. Indeed, studies from social psychology suggest that the importance of money and status competition depend on the social environment of individuals, that money compensates for the lack of social relations, and that social capital is related to both money and comparisons. Hence, we test the hypotheses that social capital moderates the effects of income and social comparisons for wellbeing, essentially changing the association between the variables. Our main hypothesis is that social capital moderates the negative impact of social comparisons. According to this hypothesis, comparing to others affects the wellbeing of people with poor social capital more than that of individuals with thriving social lives. We test this hypothesis using ordinary least squares regression equations on three cross-sectional and one longitudinal datasets. We additionally test the robustness of our results with the Lewbel instrumental variable technique, which allows to instrument for social capital in a way that does not require exogenous instruments (Lewbel, 2012). The results of this paper confirm that social capital is indeed a strong moderator in the analysed relationships. Controlling for demographic factors, we find that socially isolated people (that is, those with lower social capital) are more likely to be concerned about whether they earn more or less than others. Conversely, comparisons matter less for the wellbeing of individuals with high social capital. In a second part of the paper we test whether the wellbeing difference between rich and poor people in high social capital countries is smaller than in low social capital countries. We find evidence that this is true and we argue that this is the consequence of the lower importance of social comparisons for wellbeing when citizens are highly endowed in social capital. Importantly, the evidence from this chapter is tested on several measures of subjective wellbeing as well as different proxies for social capital, and on both cross sectional and panel datasets. The results are comparable and consistent across measures of social comparisons, social capital and wellbeing and across datasets, and all our results suggest that social capital attenuates the negative consequences of social comparisons for subjective wellbeing, as well reduces the importance of income for wellbeing.

A version of this paper is under review at PlosOne.

Chapter 3 presents an analysis of the subjective wellbeing consequences of the Coronavirus pandemic. In this chapter I analyse two subjective wellbeing measures, mental distress and life satisfaction. Since the outbreak of the pandemic, many studies have reported the negative consequences it had on subjective wellbeing. I analyse how the relationship between the health crisis and subjective wellbeing changed with individuals' social capital levels. The Coronavirus setting allows for an extreme experiment for which people are exogenously deprived their social capital, or at least the behavioural expression of it, which entails individuals' interpersonal social interactions. I test two main hypotheses: the first hypothesis is that people with high social capital suffered larger decreases in their subjective wellbeing with respect to their pre-pandemic levels than did people with low social capital, due to the reduced social interpersonal interactions. The second hypothesis is that people with high social capital had on average lower levels of mental distress and higher life satisfaction over the whole period, which highlights the sheltering effect of social capital for subjective wellbeing. The hypotheses I test rest on the notion, little discussed in the literature, that social capital operates for wellbeing in two ways: firstly, the positive effect that social capital exerts for wellbeing goes through frequent interpersonal social interactions; and secondly, from the value of having networks with whom to interact. This value remains within people even when they cannot physically engage with their networks. More specifically, on the one hand the wellbeing benefits of social capital, in form of social interactions, are observable when people engage in social activities everyday. On the other hand however, social capital could entail higher wellbeing by leaving intrinsic values within people as a result of having engaged with their social networks. I conduct the analysis on a panel of UK individuals, exploiting the UK Household Longitudinal Study monthly data collected throughout the pandemic period. I construct four measures for social capital which account for the components of the latent concept of social capital, and provide evidence on how each of these differently affected subjective wellbeing. Results suggest that, firstly, high social capital people suffered larger wellbeing losses compared to their pre-pandemic wellbeing and secondly, the sheltering effect of social capital guarantees a good maintenance of wellbeing levels for the high social capital group of people, who had on average higher levels of subjective wellbeing over the whole period. In particular, results show that the components of social capital that relate to the personal sphere of interpersonal relationships (measured in a similar way to *sociability* or *relational goods* defined above) were the ones that at the same time correlated to a higher wellbeing loss compared to pre-pandemic periods levels, and guaranteed higher wellbeing levels on average compared to those who don't have social capital. I report these results in terms of mental distress and life satisfaction, as well as for each social capital component separately. I furthermore discuss the results from some robustness checks which take into account the possible endogeneity between social capital and subjective wellbeing. These results show that depriving people of their social interactions for long periods of time is harmful for their wellbeing, but that the sheltering effect of social capital still allows for higher wellbeing levels compared to not having high social capital. This chapter is particularly devoted to a thorough discussion of the concept and measurement of social capital, and to the transmission mechanisms through which it affects wellbeing during a health crisis.

Chapter 4 is devoted to understanding the role of loneliness for mental distress during the pandemic crisis. Loneliness refers to a subjective unpleasant experience that results from a perceived deficiency in one's social relationship (Paloutzian et al., 1982). In this sense, loneliness is used here as a measure of low social capital. In this chapter I use the data and results from a recently published paper on the heterogeneous mental health development of the UK population during Covid-19 (Ellwardt and Präg, 2021), to posteriorly assess how individuals' loneliness relates to the probability of occurrence of each mental distress trajectory that makes up for the observed heterogeneity in the population. In their paper, Ellwardt and Präg (2021) analyse mental distress trajectories using a latent class mixture model, a non-paramentric approach which aims at describing the distribution of individuals into clusters of people who followed the same development of mental health. Similarly to them, I identify a total of four distress trajectories. I then ex-post relate the assignment of individuals into either one of the trajectories to a set of socioeconomic variables, as well as to their pre-pandemic levels of loneliness. Results from a multinomial logistic model of individuals' assignment into a trajectory suggest that the probability of being on the continuously high mental distress trajectory is 26.67% higher for people who are often lonely than for non-lonely people. On the contrary, lonely people have a very low (4.9%) probability of being on the continuously low mental distress trajectory. This short paper underlines that, other than the risk factors that have been commonly associated to poorer mental health, people who typically suffer from poor social relations, i.e. who declared they felt sometimes or often lonely before the pandemic, had much higher chances of suffering from very poor mental health before and during the pandemic. By contrast, the chances of detecting lonely individuals in a continuously good mental health group was extremely small. The increasing epidemic of loneliness (Surkalim et al., 2022) and its social and economic costs calls for policies that aim at facilitating and improving the number and quality of interpersonal relations. In the conclusion I provide insights on the health and behavioural consequences of loneliness (which include depression, suicidal ideation, cardiovascular diseases, coronary heart disease, metabolic syndrome, and increased all-cause mortality (Bu et al., 2020; McClelland et al., 2020; Steptoe et al., 2013)), and provides evidence of the social and economic costs of bad mental health (Layard, 2017) and loneliness (Shaw et al., 2017).

The last chapter, coauthored with Stefano Bartolini and Francesco Sarracino, examines the role of social capital in explaining the differences in governments' policies for the containment of Covid-19 contagions in Europe. Given the economic and psychological costs of severe epidemic containment policies that rely on enforced social and economic restrictions, it is important to understand what is at the base of the differences in governments' choices. The paper argues that the reason for these differences rests in the different levels of trust, a form of social capital, of countries. In particular, the contribution is to analyse the role of trust in others and in institutions. The hypothesis is that countries with higher levels of trust in others and institutions will impose less stringent containment policies. We collected data on policy stringency, speed of decline of new contagions and mortality during the first wave of Covid-19 in Europe. After accounting for various confounding factors, results suggest that governments of more trustful countries introduced less stringent policies, burdening the society with lower economic and psychological costs. This did not come at the expense of public health: holding policy stringency constant, high trust countries report lower mortality, as well as lower number and faster decline of new contagions than others. The conclusion is that the trade-off between freedom and health during epidemics depends on a country's trust level: the more people trust others and institutions, the more this trade-off fades. Therefore, promoting trust in others and in institutions is a critical challenge for contemporary societies.

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Chapter 2

Social capital reduces the impact of social comparisons on subjective wellbeing: Evidence from international datasets

This chapter has been co-authored with Stefano Bartolini, Marcin Piekałkiewicz and Francesco Sarracino. A slightly updated version of this paper has been submitted to a journal and is now under revision.

Abstract

Social comparisons have negative consequences for happiness, health, and economic decisions. Is there a remedy? We assess whether people with high social capital suffer less from social comparisons than others. Using approximately 400000 interviews from nationally representative surveys and controlling for demographic factors, we find that socially isolated people are more likely to be concerned about their income levels, and whether they earn more or less than others. Conversely, keeping up with the Joneses matters less for the wellbeing of individuals with high social capital. This result is reflected at country level: in countries that are rich in social capital, the differences in wellbeing between income groups are small, which is a consequence of the relatively small impact of social comparisons on wellbeing. This evidence suggests that social capital attenuates the negative consequences of social comparisons for subjective wellbeing.

Keywords: *Subjective wellbeing; Social capital; Social comparisons; Absolute income; Lewbel method of generated instruments; GSOEP; EU-SILC; ESS; EVS-WVS*

2.1 Introduction

The literature has highlighted that there are two types of income that influence the subjective wellbeing of individuals. The first is absolute income, which measures individuals' purchasing power, and is positively related to subjective wellbeing. The second is the income of self-relevant others, that is the income of the reference group, which affects wellbeing via comparisons. Considerable research has devoted attention the effects of comparisons for wellbeing, with mixed results. Despite some researchers found that comparisons are positively related to wellbeing (Barrington-Leigh and Helliwell, 2008; Hirschman and Rothschild, 1973; Ligon et al., 2002; Kingdon and Knight, 2007; FitzRoy et al., 2014; Senik, 2008), most economic literature agrees that relative income and income comparisons have a negative effect on wellbeing (Clark et al., 2008; Clark and Senik, 2010; Luttmer, 2005; Easterlin, 1995; Falk and Knell, 2004).

Although considerable attention has been devoted to answer the questions of the effects of income and comparisons for wellbeing, generally studies have not considered the hypothesis that such answers are conditional on social capital. In the subjective wellbeing literature social capital, absolute income and comparisons are considered mutually independent factors that influence wellbeing, with social capital playing a well-established positive role for wellbeing (Helliwell and Aknin, 2018). In other words, researchers have overlooked the possibility that the relationship between wellbeing and both absolute income and comparisons may depend on social capital. In this paper we explore this possibility and test the hypotheses that social capital changes the association between absolute income and wellbeing, and the one between comparisons and wellbeing.

The reason for which we believe this may be the case is that studies form social psychology find that social capital is related to both materialism and social comparisons. Social capital is commonly defined as "networks together with shared norms, values and understandings that facilitate co-operation within or among groups" (OECD, 2001) and it entails the formal and informal social relationships, the shared norms of reciprocity and trust within a community, and the emotional support, material and behavioral assistance between people (Putnam et al., 2000, 1994). Materialistic individuals attach high importance in their life to both their absolute and relative achievements, and to their social standing (Kasser, 2002). The psychological literature that investigates the link between social capital and materialism finds a negative relationship, suggesting that absolute income and social status may offer psychological compensation to the distress caused by poor social capital (Sheldon and Kasser, 1995; Kasser and Ryan, 1993). This literature is often based on small samples that limit the possibility to draw general conclusions, and there is little evidence of a causal link between the variables. To this regard, using a longitudinal sample of individuals Pieters (2013) provides evidence that materialism and loneliness are intertwined over time, with loneliness contributing to materialism more than the other way around. Moreover, some experimental evidence suggests that materialism causes a reduction of helpfulness and generosity (Vohs et al., 2006), and interest in relational activities (Bauer et al., 2012), which are two common measures of social capital. Lastly, findings from social psychology suggest the hypothesis that social capital moderates the impact of social comparisons on subjective wellbeing. According to this hypothesis, positional competition affects the wellbeing of people with poor social capital more than that of individuals with thriving social lives. Status and success offer compensation to people with poor social experience in different ways according to their levels of social capital.

We build on the psychology and social psychology literature to provide evidence that social capital changes the relationships between income and wellbeing, and the one between comparisons and wellbeing. Essentially, we test whether social capital is a moderator in the two relationships and we expect it to reduce the correlation of absolute income and social comparisons with subjective wellbeing.

To the best of our knowledge only Barcena-Martin and colleagues tested the hypothesis for which social capital moderates the impact of social comparisons for wellbeing (Bárcena-Martín et al., 2017). Retrieving data from the German Socio-Economic Panel, the authors test the hypothesis that two types of social capital, bridging and bonding, moderate the effects of relative income on wellbeing. Bonding social capital concerns relationships among individuals belonging to a group or community, whereas bridging social capital refers to relationships among individuals belonging to different social groups (by social class, race, religion, etc.). They find that bridging social capital moderates the relationship between subjective wellbeing and social comparisons, while bonding social capital does not exert a significant association. Their finding hinges on data issued from one country (Germany) in a specific period of time. Thus, the wordings and measures of the considered variables as well as their geographical restriction limit the general validity of the study. Moreover, the results may be biased by the possible endogeneity of social capital. Additionally, they limit their analysis to relative income and do not consider the possibility that social capital moderates the relationship between one's own income and subjective wellbeing. We overcome these two limitations by extending the geographical scope of the analysis, and by accounting for the endogeneity of social capital, and by checking whether the absolute income - subjective wellbeing relationship is affected by social capital. We use panel data from Germany and publicly available data from three international surveys, for a total of nearly 500,000 respondents from industrial countries. This allows us to study our relation of interest in a variety of settings, using various measures of subjective well-being, of social capital, and of social comparisons. We also provide some evidence suggesting that the moderating role of social capital is, at least in part, causal.

In addition, we check whether the life satisfaction gap between rich and poor people is negatively correlated with the level of social capital prevalent in a country. If the subjective well-being of people with high social capital is less strongly associated to income, then income should play a lesser role in individual's wellbeing differences at country level.

In the remaining of the paper we will refer to social comparisons as a term that encompasses measures of reference income, self-reported social class and income rank, a measure of the relative position of an individual in their national income distribution. We detail their measurements later on in the paper. As for social capital, common proxies for social capital used in the literature are sociability, measured for instance by the frequency of attending social activities, meetings with friends, or relatives or neighbors, as well as volunteering, cooperative attitudes of people, and various measures of trust in others and in institutions (Alesina and La Ferrara, 2002; Helliwell et al., 2014; Helliwell and Wang, 2010; Bjørnskov, 2003; Helliwell, 2003; Helliwell and Putnam, 2004). Following this approach, we analyse multiple proxies for social capital, including measures of sociability, interpersonal trust and individuals' associational activity.

In the next section, we present the data and the empirical method for the individual level analysis, for the instrumental variable approach, and for the macro-level analysis. In section 2.3, we illustrate the results of our analysis. In section 2.3.1 we discuss the robustness of our findings to endogeneity issues, whereas in section 2.3.2 we present the results of cross-country analysis testing the implications of our finding for wellbeing inequality. Specifically, as social capital reduces the importance of social comparisons for subjective wellbeing, the higher the social capital in a country, the lower the wellbeing gap between rich and poor citizens. In section 2.4 we discuss our findings and their implications for policy. The last section provides some final remarks.

2.2 Methods and data

To empirically test the hypothesis that social capital moderates the relationship between social comparisons and subjective wellbeing, we estimate various subjective wellbeing regressions in which we interact social capital with measures of social comparisons. We also interact social capital with absolute income. In simple terms, we are interested in observing whether and to what extent the inclusion of social capital alters the relationship between social comparisons and subjective wellbeing, and that between absolute income and subjective wellbeing.

We draw data from four, freely available and widely used datasets (see section 2.2.5 for more details). Namely, we exploit the European Union Survey on Income and Living Conditions (EU-SILC), the European Social Survey (ESS), the integrated European Values Study - World Values Study (EVS-WVS), and the German Socio-Economic Panel (SOEP). Besides being freely available and known to most social scientists, these datasets allow us to test the robustness of our findings to different samples, wordings and measures of subjective wellbeing, social capital and social comparisons. The first three datasets provide internationally comparable data, which allow us to test our hypothesis on a rich set of countries. SOEP provides panel data from Germany, and allows us to account for individual fixed effects.

Available measures of social comparisons include reference income, income rank, and self-reported social class. These measures all relate to individuals' tendency to compare to others when assessing their relative economic or social standing. In particular, reference income, measured as the average income of the reference group, is a frequently used measure of social comparisons because it is a benchmark against which individuals evaluate their income levels. Income ranks follow the same reasoning, as respondents state their income choosing from income brackets that have been created on the national income distribution level. Hence, when answering the income question, they are comparing to the national income distribution. Lastly, self-reported social class involves individuals comparing their own social status to that of others in their social and economic context and it refers to their subjective perception of their own social position in society.

Reference income and income ranks are objective measures of comparisons. Self-reported social class provides information on subjective perceptions of one's position along the income ladder. We emphasize that the use of both objective and subjective measures of social comparisons allows us to account for two approaches to the way individuals select comparison targets (Fujita and Diener, 1997). The first approach assumes that objective characteristics such as proximity (e.g. area of residence) or similarity (gender, age, etc.) determine comparison targets. The second approach underlines the role of subjective perceptions and preferences in the selection of comparison targets from a range of possible alternatives. In the next two sections we detail respectively the methods and the data used in our analysis.

2.2.1 Empirical Models

We apply Ordinary Least Squares (OLS) regression analysis with interaction effects to test the hypothesis that social capital changes the association between subjective wellbeing and both absolute income and social comparisons. Equation 2.1 provides a general form of the equation we tested. The exact definition of the variables, as well as the list of control variables changes depending on the dataset. These aspects are presented in section 2.2.5.

$$
\begin{aligned}
SWB_i = \alpha &+ \beta_1 \cdot Abs.Income_i + \beta_2 \cdot SocComp_i + \beta_3 \cdot SCindex_i + \\
&+ \beta_4 \cdot SCIndex_i \cdot Abs.Income_i + \beta_5 \cdot SCindex_i \cdot SocComp_i + \\
&+ \gamma' \mathbf{X_i} + \varepsilon_i
\end{aligned}
\tag{2.1}
$$

where SWB stands for subjective wellbeing; the subscript i stands for individuals; $Abs.Income$ and $SocComp$ stand for absolute income and social comparisons, respectively; $SCindex$ is a categorical variable where higher values indicate a higher level of social capital; $\mathbf{X}$ is a vector of control variables such as age, gender, marital status, education level, a health variable, country and year dummies (when they apply). The full list of controls included is specified in the data section and in the notes to table 2.1. Lastly, ε is the error term. All estimates make use of heteroskedasticity robust standard errors.

The impact of absolute and reference income has been extensively studied in the subjective wellbeing literature (Clark et al., 2008; Senik, 2009). Evidence shows there is a positive effect of income on subjective wellbeing and this is likely to be causal, at least in the short term (Nikolova and Graham, 2021; Powdthavee, 2010; Frijters et al., 2004). Reference income instead is found to be detrimental to subjective wellbeing, at least in the majority of the cases (Clark et al., 2008; Clark and Oswald, 1996). In fact, some researchers argue that reference income may be seen as a signal of opportunities for personal future income, and therefore have a positive effect on subjective wellbeing (Barrington-Leigh and Helliwell, 2008; Senik, 2008). The value-added of our work is to show how these relationships change with the introduction of social capital. Social capital is typically found to exert a positive effect on subjective wellbeing (Helliwell and Aknin, 2018). A thorough discussion of the main results and of the expected signs of control variables is available in section 2.3.

In Eq. 2.1 we refer to SWB as a general term encompassing various measures of self-reported wellbeing. Each dataset has different proxies to monitor subjective wellbeing, such as life satisfaction and happiness. The specific measures available for this study are presented in section 2.2.5.

Interaction terms (β_4 and β_5) indicate whether the impact of absolute income and social comparisons on subjective wellbeing changes with the level of social capital. The marginal effects of absolute income and social comparisons on subjective wellbeing are then respectively equal to the expressions $\beta_1 + \beta_4 \cdot SCindex_i$ and $\beta_2 + \beta_5 \cdot SCindex_i$. The percentage of the moderation effect is calculated as a ratio of the interaction coefficient to the absolute income or social comparisons coefficient (a detailed explanation is provided in the section 2.2.2 and actual computations follow in section 2.3). For ease of interpretation of the results, and in particular of interaction effects, we estimate Eq. 2.1 using OLS, thus treating subjective wellbeing as a cardinal variable. Our results, however, are qualitatively unchanged if we use ordered probit regressions. For the analysis of SOEP data, we modify Eq. 2.1 to include individual fixed effects to account for time invariant unobserved heterogeneity. This is possible because of the longitudinal dimension of the data. Also in this case we use robust standard errors.

2.2.2 Moderation effects

We quantify the role of social capital for the association between subjective wellbeing and income (both absolute and reference) by means of moderation effects. Moderation effects indicate by how much each level of the social capital index reduces the income coefficients of the subjective wellbeing regression.

The computation of moderation effects proceeds as follows:

1. the main effects (β_1 and β_2) from Eq. 2.1 provide the baseline correlation between

absolute income and social comparisons, and subjective wellbeing;

2. we add the interaction effects (β_4, s and β_5, s) to the main effects to compute the correlation of social comparisons with subjective wellbeing for the various levels s of the index of social capital ($\tau_{abs,s} = \beta_1 + \beta_4$ and $\tau_{soccap,s} = \beta_2 + \beta_5$). For instance, if the index of social capital is on a scale from 0 to 4, we add the interaction coefficients of each level s to the main effects.

3. we compute the moderation effect (φ) of each level of social capital s as follows:

$$\varphi_{js} = 100 - \frac{\tau_{js} \cdot 100}{\beta_m}$$

where j stands for absolute income and social comparisons, respectively, and m indicates the two main effects. We compute the standard errors of the moderation effects using the error propagation model. For details, please refer to section A.5 of the Appendix.

2.2.3 Addressing Endogeneity Issues: the Lewbel Method of heteroskedasticity generated instruments

There are various reasons to believe that social capital is endogenous to wellbeing, as the association between social capital, social comparisons and subjective wellbeing may be driven by omitted variables or reverse causality. We account for endogeneity using a Two-Stages Least Squares (2SLS) instrumental variable approach. Specifically, we instrument the main effect of social capital, and its interaction terms with absolute and social comparisons.

Identifying a proper instrument for social capital is difficult, as most of the factors affecting people's social life will likely affect their wellbeing as well. To overcome this problem we use the method of generated instruments proposed by Lewbel (2012). This approach allows to identify a causal model without imposing the exclusion restriction which is typically required in a standard 2SLS, while instead exploiting the heteroskedasticity of the first step equation to construct the instruments (Lewbel, 2012). This approach has been used numerous times now (as documented in Lewbel (2012)) in various applied economics settings such as in health economics (Brown, 2014; Schroeter et al., 2013), agricultural economics (Emran and Shilpi, 2012; Emran and Hou, 2013) and happiness economics (Schroeter et al., 2013; Tiefenbach and Kohlbacher, 2015; O'Connor, 2020a,b; Arampatzi et al., 2018; Elsas, 2021). One downside of this approach is that the generated instruments do not have an economic meaning. This limitation was acknowledged in the original paper by Lewbel (2012), and in any case, the approach is only used in this paper as a robustness check.

Formally, we implement the two-stage estimator proposed by Lewbel in the following way: to begin, we regress each endogenous variable on the vector of control variables $\mathbf{X}$ from our main equation of subjective wellbeing, and the vector of residuals μ_i are retrieved. More specifically, we run the following first-stage regressions:

$$\text{S}ocialCapital_i = \alpha_1 + \theta' \cdot \mathbf{X_i} + \mu_{1,i} \tag{2.2}$$

$$(SocialCapital * AsboluteIncome)_i = \alpha_1 + \theta' \cdot \mathbf{X_i} + \mu_{2,i} \tag{2.3}$$

$$(SocialCapital * SocialComparisons)_i = \alpha_1 + \theta' \cdot \mathbf{X_i} + \mu_{3,i} \tag{2.4}$$

If the residuals from Eq. 2.2, 2.3, 2.4 are heteroskedastic, instruments can be generated by multiplying them with each of the mean-centered observed variables (X_j), as follows:

$$Z_j = (X_j - \bar{X_j}) \cdot \hat{\mu} \tag{2.5}$$

where j corresponds to a given control variable from vector $\mathbf{X}$, and $\hat{\mu}$ are the stored vectors of residuals from Eq. 2.2, 2.3 and 2.4. Hence, for each endogenous variable the number of generated instruments Z is equal to the number of control variables included in the vector $\mathbf{X}$. By construction, the covariance between the residuals $\hat{\mu}$ and the demeaned controls is zero, but with heteroskedasticity the instruments $\mathbf{Z}$ will take meaningful values. The vector $\mathbf{Z}$ of generated instruments is then used to instrument the endogenous variables in the second step of the 2SLS framework as follows:

$$SWB_i = \alpha_2 + \pi \cdot Endoge\widehat{nous\ V}ariables_i + \theta \cdot \mathbf{X_i} + \nu_i \tag{2.6}$$

The Lewbel approach relies on the same assumptions of a standard instrumental variable model, with the addition of two extra conditions. The first is that there exists heteroskedasticity in the first stage equation, that is $Cov(\mathbf{Z}, \mu^2) \neq 0$, where $\mathbf{Z}$ is the vector of instruments constructed from some or all of the variables included in the vector of controls of the structural equation $\mathbf{X}$. The second condition is that there exists a $\mathbf{Z} \subseteq \mathbf{X}$ for which $Cov(\mathbf{Z}, \mu\epsilon) = 0$, where ϵ is the error term of the structural equation of wellbeing, which would allow the constructed instruments to satisfy the exclusion restriction.

The intuition behind the mechanics of the Lewbel approach comes from a standard linear regression mechanics: the residuals are by construction exogenous to the right hand side variables in the model is correctly specified. This means that if the structural form is correctly specified, the remaining errors are idiosyncratic (Lewbel, 2012). Hence, if the chosen $\mathbf{X}$ are exogenous in the structural equation, the instruments created on those $\mathbf{X}$ are also exogenous, and will affect the outcome variable only via the endogenous regressor. As Lewbel and Baum and Lewbel discuss, if this assumption does not hold, that is if $Cov(\mathbf{Z}, \mu\epsilon) \neq 0$, bounds on the causal parameters can still be obtained as long as this covariance is not too large (Lewbel, 2012; Baum and Lewbel, 2019). Lastly, if the residuals are heteroskedastic, they contain information about the the variation of the outcome (endogneous) variable, which makes the instruments relevant. Although the second condition is in practice untestable, we use the typical IV diagnostics to assess whether the instruments are relevant (first stage F-statistics) and valid (Hansen overidentification test).

A plausible cause of heteroskedasticity in equations 2.2, 2.3 and 2.4 may come from omitted variables, or from the non constant variance in the distribution of the residuals of social capital over the age distribution. We test this with a Breush-Pagan test, which confirms this hypothesis with p-values consistently smaller than 0.001. Additionally, age is exogenously determined with respect to subjective wellbeing, which makes it a valid source to construct the instrument on. Hence, we construct the instruments $\mathbf{Z}$ on demeaned age and age squared, multiplied by the residuals of equations 2.2, 2.3 and 2.4.

To limit the number of instruments necessary for our 2SLS estimations, we use the index of social capital as a continuous variable. We remind the reader that we have three endogenous variables in our specification: social capital and its two interactions with social comparisons and absolute income. By using the index of social capital as a continuous variable we can limit the number of instruments necessary for identification to six (or eight in case of the ESS).

We use a 2SLS model even if subjective wellbeing is not a continuous variable as the coefficients estimated with a linear model are comparable to the marginal effects produced by non linear instrumental variable models (Angrist, 2001). We expect the coefficient of social capital to be biased upwards. Indeed, if we assume a bias given by the omission of unobserved personality traits, the direction with which they affect social capital and life satisfaction is likely the same. For instance, a more extrovert person may be more likely to have an active social life, but he may also be happier. Likewise, a neurotic person will probably tend to have less social capital and lower levels of subjective wellbeing.

2.2.4 Country-level analysis

We are furthermore interested in the following cross-country implication of our individual level analysis: if social capital reduces the correlation coefficient between subjective wellbeing and social comparisons, then we should expect that wellbeing differences are less affected by income differences in countries in which social capital is higher than in others. We test this implication at a macro-level using countries' life satisfaction difference between rich and poor people as a measure of the differences in subjective wellbeing between income groups. We use regression analysis of the rich/poor life satisfaction gap on countries' share of individuals who have high social capital, in which we partial out the possible confounding effect of countries' prosperity and income inequality. Formally, we test the following equation using OLS with robust standard errors:

$$\Delta SWB_c = \alpha + \beta_1 \cdot log(GDPpercapita_c) + \beta_2 \cdot Gini_c + \beta_3 \cdot SC_c + \varepsilon_c \tag{2.7}$$

where the unit of analysis are countries (c), ΔSWB is the subjective wellbeing difference between people belonging to the first and to the fifth income quintile in a given country, and SC is the share of people with high social capital (SC index = 2). We expect that the social capital variable attracts a negative coefficient, indicating that a greater share of individuals with high social capital is associated to a smaller subjective wellbeing gap. We control for the Gini index of the income distribution to account for the likely influence of income differences on wellbeing differences. Moreover, we control for countries' GDP, as more prosperous countries are expected to exhibit lower happiness inequality (Clark, 2017).

2.2.5 Data

European Union Statistics on Income and Living Conditions

The European Union Statistics on Income and Living Conditions (EU-SILC) is a general population survey mandated by the European Commission to collect timely and internationally comparable data on income, social exclusion and living conditions in European Union member states.

The EU-SILC is a yearly survey with a rolling sample and rotating modules. The rolling sample ensures that part of the sample can be followed longitudinally for a maximum of four years. The rotating modules permit to collect data on specific topics. In particular, information about subjective wellbeing and social capital were first administered in 2013 and subsequently in 2018. However, the latter wave of data has not been made available for research. Therefore, we use cross-sectional micro-data from the 2013 EU-SILC for the purposes of present analysis.

The EU-SILC (2013) sample includes approximately 318,000 observations coming from 29 European countries (Table A.5 in the Appendix provides detailed descriptive statistics). The data provide three variables related to subjective wellbeing, namely life satisfaction, frequency of feeling downhearted or depressed, and job satisfaction. We are aware that job satisfaction is a measure of satisfaction in a specific life domain, rather than an encompassing evaluation of life as a whole. Nonetheless, we decided to include it in the analysis because it is an important aspect of people's life, and one that can be easily affected by social comparisons, especially on the workplace.

Life satisfaction is observed through answers to the question: "Overall, how satisfied are you with your life these days? Please answer on a scale of 0 to 10, where 0 means 'Not at all satisfied' and 10 means 'Completely satisfied'." The second measure of (lack of) subjective wellbeing is based on answers to the question: "How much of the time over the past four weeks have you been downhearted and depressed? Please answer on a scale from 1 to 5, where 1 means 'All of the time' and 5 means 'None of the time'." We reverted the scores so that higher values indicate higher ill-being. Job satisfaction follows the same wording of the question about life satisfaction, but asks explicitly about present work. Also in this case the answers range on a scale of 0 to 10, where 0 means 'Not at all satisfied' and 10 means 'Completely satisfied'." As job satisfaction pertains to people in employment, our analysis is restricted to a sub-sample of workers made of about 152,000 individuals.

Our main explanatory variable is social capital. The EU-SILC provides two measures of social capital, trust in others and frequency of meeting with friends, which we combine in a single index. The trust question asks: "Would you say that most people can be trusted? Please answer on a scale from 0 to 10, where 0 means that in general 'You do not trust any other person' and 10 that you feel 'Most people can be trusted'." We construct a dummy variable equal to one for answers larger than five, the median value, zero otherwise. The frequency of meeting with friends is based on the answers to the question: "Do you meet up with friends/family for a drink/meal (at home or outside) at least once a month? (Yes/No)". We build a dummy variable equal to one if an individual meets his friends or family at least once per month, zero otherwise. The social capital index simply adds up the two dummies. Hence, the index is a categorical variable taking values from zero to two, where higher values stand for more social capital.

Income is the monthly disposable equivalised income adjusted to purchasing power parities by country. The equivalised disposable income is the total income of a household, after tax and other deductions, that is available for spending or saving, divided by the number of equivalent adults. Household members are made equivalent by weighting each of them using the so-called modified OECD equivalence scale. The scale applies a weight of 1.0 to the first adult; 0.5 to the second and each subsequent person aged 14 and over; 0.3 to each child aged under 14. To correct for purchasing power parities we use price level indices for the actual individual consumption (EU28=100) from Eurostat.

We proxy social comparisons with reference income. This variable is computed as the average income of the reference group. We assume that respondents compare their incomes with those of other people of the same sex and age group living in the same region. This definition provides a total of 990 reference groups. The average number of individuals in a reference group is about 312.

To account for individual heterogeneity, we use a standard set of control variables including respondent's age, gender, marital status, education level, occupation, home ownership, being chronically sick or disabled, i.e. an objective measure of health (Buunk et al., 2013; Carrieri, 2012) and the country of residence. This set of socio-demographic characteristics is common to all the datasets available for present analysis. The only exception is the control for health which, in case of the Integrated World Values Survey - European Values Study (WVS-EVS), is self-reported subjective health. As this variable is likely to be endogenous to subjective wellbeing, we do not control for health status in the analysis of WVS-EVS data. The detailed list of control variables by dataset is provided in the note to table 2.1.

European Social Survey

The European Social Survey (ESS) is a bi-annual survey administered in various European countries since 2002. Each wave of the ESS provides internationally comparable, and nationally representative data on adult population. It provides a rich set of information about people's lives, feelings, values and preferences. Specifically, the ESS provides data on income, life satisfaction and happiness, various measures of social capital, along with other individual level data.

We use the 9th round of the European Social Survey which was administered in 2018. This is the latest available wave before the pandemic (2020). In each wave the ESS randomly interviews about 2000 individuals per country. In 2018 the sample included about 38,000 individuals from 29 European countries. Table A.17 in the Appendix provides detailed descriptive statistics.

The ESS provides two measures of subjective wellbeing, life satisfaction and happiness. Both variables record respondents' answers using a 0 to 10 scale where higher scores indicate higher wellbeing. Life satisfaction is observed through answers to the question: "All things considered, how satisfied are you with your life as a whole nowadays? Please answer using this card, where 0 means 'extremely dissatisfied' and 10 means 'extremely satisfied'." The wording of the happiness question is: "Taking all things together, how happy would you say you are? 0 Extremely unhappy, 10 Extremely happy".

As for the measure of social capital, we use similar proxies to those used in the analysis of EU-SILC data. The answers to the question "How often do you meet socially with friends, relatives or work colleagues?" are recoded in a dummy variable set to one if a respondent meets socially at least once per week. The ESS provides three questions that provide an overall evaluation of how much respondents trust others. The wordings are: "Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people?"; "Do you think that most people would try to take advantage of you if they got the chance, or would they try to be fair?"; and "Would you say that most of the time people try to be helpful or that they are mostly looking out for themselves?". Answers range on a scale from zero to ten, in which higher scores indicate higher levels of perceived trustworthiness, fairness, and helpfulness. After factor analysis, we compute a synthetic index of social trust by averaging the answers to each question. Subsequently, we create a dummy variable (labelled "social trust") set equal to one if the synthetic index ranges between 6 and 10, zero otherwise. Finally, we create the index of social capital as the sum of the dummies about frequency of meeting friends, and social trust. The index takes values from the set $s = 0, 1, 2$ where higher values indicate more social capital.

The ESS questionnaire asks the respondent to choose the interval corresponding to his or her household's total income. There are ten intervals which are country specific and delimited by income deciles. In other words, each income interval is relative to the national income distribution. Thus, our measure of social comparisons is the income rank, i.e. the individual's position in the national income distribution. Income rank is a categorical variable and, for the sake of simplicity when used with interactions, we recoded it in three levels: income rank 1-3 (for the bottom three deciles), income rank 4-7 (for the middle four deciles), and income rank 8-10 (for the top three deciles).

As for income, we impute the disposable household monthly income by attributing to each respondent the average household income of the income bracket to which he/she declares to belong to (the original variable is the same used for income rank). In the case of non-Euro countries we convert the new variable to euros. Subsequently, we adjust for purchasing power parity (PPP) using the conversion factor provided by Eurostat (EU28=100).

Integrated World Values Survey - European Value Study

The World Values Survey (WVS) and the European Value Study (EVS) are two widely explored datasets made of repeated cross-sectional surveys that started in 1981. Although separate, the two surveys can be integrated, as they are largely harmonized. The integrated WVS-EVS covers roughly every country in the World, and provides a nearly unique source of comparative information about people's feelings, believes, values, and attitudes.

At present the WVS and the EVS comprise respectively 7 and 6 waves, covering the period 1981 - 2021. In particular, the 3rd, 5th and 6th waves of the World Values Survey – European Values Study integrated dataset provide the sole source of free data that we are aware of with information about self-reported social class. We use this information to directly observe respondent's relative placement in a society, i.e. a subjectively perceived form of social comparisons. In the course of the interviews, respondents are asked the following question: "People sometimes describe themselves as belonging to the working class, the middle class, or the upper or lower class. Would you describe yourself as belonging to the: 1. Upper class; 2. Upper middle class; 3. Lower middle class; 4. Working class; 5. Lower class; 6. No answer". We record the last category to missing.

The three selected waves provide information about 417,000 respondents from 68 countries world-wide. For the purposes of present analysis, we focus on a subset of 20 developed countries, for a total of nearly 50,000 respondents. Table A.26 in the Appendix provides detailed descriptive statistics, and Table A.27 lists the countries included in the analysis.

The integrated WVS-EVS provides two proxies of subjective wellbeing, namely life satisfaction, and happiness. The wording for the former is: "All things considered, how satisfied are you with your life as a whole these days?" Possible answers range on a 1 to 10 scale in which the lowest value corresponds to "dissatisfied" and the highest to "satisfied". Happiness is observed via answers to the following question: "All considered you would say that you are: 1. very happy; 2. pretty happy; 3. not too happy; 4. not at all happy?" This variable has been recoded so that the category "very happy" corresponds to the highest value in the scale, and the category "not at all happy" corresponds to the lowest one.

Our measure of social capital follows the same specification adopted in the analysis of

EU-SILC and ESS data. In particular, the WVS-EVS integrated dataset contains information about trust in others based on the following question: “Generally speaking, would you say that most people can be trusted, or that you can’t be too careful in dealing with people?”, with answers coded as 1 (“most people can be trusted”), and 0 (“you can’t be too careful”). Additionally, we consider respondents’ participation in various groups and associations. During interviews, people are asked whether they are members or not of a list of groups or associations. We created a dummy variable taking values of 1 if the respondent declares to participate in at least one Putnam’s group or association, 0 otherwise. Putnam et al. (1994) identify in associations a source of general trust and of social ties leading to governmental and economic efficiency. Among Putnam’s groups we include: social welfare service for elderly, church organizations, sport clubs, art and literature clubs, fraternal groups and youth associations, human and animal rights. Finally, we create the index of social capital as the sum of the two dummies. The index takes values from the set $s = 0, 1, 2$, where higher values indicate more social capital.

Respondents of the WVS and EVS are asked to specify to which income bracket they belong to. Differently from the ESS, however, the income brackets do not necessarily reflect income deciles of the national income distribution. Therefore, this variable cannot be regarded as income ranking. Moreover, there is considerable variety in the way this question is administered across countries and time. Therefore, we kept its original categorical scale without applying any transformation.

German Socio-Economic Panel

The SOEP is a panel dataset administered yearly in Germany by the DIW. It was first administered in 1984 in West Germany and, as of June 1990, its sample widened to include households and individuals from East Germany. The main focus of the SOEP is to monitor demographic, economic, social and political aspects of life in Germany. Although the data span a long time period, our analysis is limited by the years when the survey recorded information about Germans’ social capital. Thus, our data cover the period from 1990 to 2011. The sample consists of 9 waves for a total of about 36,600 individuals interviewed at least two times, giving more than 129,900 observations. Table A.35 in the Appendix provides detailed descriptive statistics.

The wording of the question about life satisfaction is fairly similar to those used in previous surveys. Specifically, the questions reads: “Please answer on a scale from 0 to 10, where 0 means ‘completely dissatisfied’ and 10 means ‘completely satisfied’: How satisfied are you with your life, all things considered?”.

Our main explanatory variable, the index of social capital, is defined as the sum of four dummy variables: “Attending social gatherings”, “Helping friends”, “Performing volunteering work”, and “Participating in local politics”. Each dummy variable is set equal to one if the respondent carries out a given activity at least once per month, zero otherwise. Thus, the social capital index ranges from zero (for individuals not performing any of the activities), to four (for people who perform all four activities).

The other two main explanatory variables are absolute and reference income. The former is defined as monthly equivalised disposable income, and it is adjusted by the price level in a given year (transformed in logarithm). Reference income is computed as the average income (in logarithmic form) of the reference group. We assume that respondents compare their incomes with those of other people of the same sex, age group and living in the same geographical area (West or East Germany) in the same year. In total we have 210 reference groups (ten reference groups per year for the three waves before unification (which do not include East Germany), and twenty reference groups per year for the nine waves after unification). The average number of respondents per reference group is 755.

Data for the macro analysis

For the last step of our analysis, the key variables are: first, the share of respondents with a social capital index equal to two, i.e. the share of people with high social capital; second, the subjective wellbeing gap between rich and poor people. The gap is the difference in the weighted average of subjective wellbeing between the first and fifth quintile of the income distribution by country/region. Both variables are computed by country. In case of EU-SILC data, we repeat the analysis also at regional level. In case of the integrated WVS-EVS data, the subjective wellbeing gap is the difference in the weighted average of life satisfaction and happiness (separately) between the upper and the lower social class by country.

As the correlation between social capital and subjective wellbeing gap can be spurious, we add income inequality and gross domestic product (GDP) to control for their confounding effects. Our measure of income inequality is the Gini index of equivalized disposable income. We tested the robustness of our results to alternative specifications of this variable. Specifically, we used the ratios 90/10 and 50/10, that is the ratio between the average income of the 90th (50th) percentile with respect to the one of the 10th percentile. These data are provided by Eurostat (Eurostat, 2021a). For the analysis at regional level, we compute the regional Gini index as the weighted absolute income by region, using the EU-SILC 2013 micro data.

GDP per capita for European countries is sourced from Eurostat (Eurostat, 2021b), and is expressed in thousands of current euro corrected for purchasing power parity. We do not correct for inflation because the data refer to 2013 for the EU-SILC and to 2018 for the ESS. The analyses on the integrated WVS-EVS, and ESS data use figures from the World Development Indicators of the World Bank (The World Bank Group, 2021). In this case GDP per capita is expressed in thousands of constant US dollars for the WVS-EVS, and in current international dollars corrected for purchasing power parity for the ESS.

2.3 Results

Table 2.1 presents the estimation results of the analysis conducted on the four considered datasets. Columns 1, 2 and 3 show the estimation results of the analysis conducted on EU-SILC data (Obs. = 317,978). Columns 4 and 5 report results using the dependent variables available in ESS data (Obs. = 38597), columns 6 and 7 show results for the proxies available in the integrated WVS-EVS dataset, while the last column refers to the fixed effects model of life satisfaction estimated using SOEP data (Obs. = 129,901). The complete set of results, including the control variables, are omitted for brevity, and are available in the Appendix. Table 2.1 focuses on the key variables for our analysis. The first 6 rows of the Table, show the coefficients for the variables that are common across all datasets: absolute and reference income, and the interaction terms between the social capital index and absolute income. The subsequent rows list the main explanatory variables by dataset. This is because variables and specifications change across datasets. For instance, the last panel is dedicated to SOEP and reports the results for the interactions between the various levels of social capital index and reference income; the third panel, dedicated to ESS data, accommodates the results using income rank as a measure of social comparisons, whereas the panel dedicated to WVS-EVS shows the result of social class and the interactions between social capital index and social class. The notes at the end of Table 2.1 list the control variables used for each dataset separately.

Our findings for the EU-SILC suggest that higher absolute income correlates with greater life satisfaction (see the coefficient of absolute income $b = 0.511^{***}$) and job satisfaction ($b = 0.675^{***}$), and less depressive feelings ($b = -0.156^{***}$). Social comparisons show an opposite pattern, indicating that they are detrimental for wellbeing: the coefficients on the reference income variable are negative and statistically significant for life and job satisfaction, and positive for depressive feelings (see results in the second row, first 3 columns). The coefficients of the interaction terms between the social capital index and absolute income (rows 3 and 4) suggest that higher social capital reduces the association between absolute income and subjective wellbeing. Similarly, the coefficients of the interaction terms between social capital and reference income indicate that the correlation between social comparisons and subjective wellbeing weakens for high levels of social capital (rows 7 and 8). As previously noted, percentage moderation effects are calculated as a ratio of the interaction coefficient to the income coefficient. For example, taking results from the EU-SILC (column 1 of table 2.1), the coefficient of "Social capital index = 2 * absolute income" is -0.241, while the coefficient on "absolute income" is 0.511, meaning that for those who have high social capital (SCindex = 2) the income effect is $-0.241 + 0.511 = 0.27$. This indicates that the original absolute income coefficient has decreased by 0.241, which in percentage terms is equal to $0.241/0.511 = 47.16\%$ (as seen in column 2 of Table 2.2, on the first row referring to absolute income).

These findings hold also when using the ESS (columns 4 and 5) and the WVS-EVS (columns 6 and 7). Absolute income is found to exert a positive effect on subjective wellbeing ($b = 0.529^{***}$ for life satisfaction and $b = 0.491^{***}$ for happiness), while social comparisons, measured as income rank in the ESS and self-reported social class in the WVS-EVS, negatively correlate with subjective wellbeing. The interaction terms exhibit the same patterns of results as for EU-SILC data, suggesting an easing of the social comparison effect on subjective wellbeing when social capital is high (see rows 13-14 and 16-17). In particular, in the ESS, social comparisons are proxied by three categories of income rank, 1-3, 4-7 and 8-10. We use income rank 4-7 as base category, so that people who belong to the lowest (1-3) and the highest (8-10) income rank both compare to those in the middle of the income distribution. Hence, the coefficient of income rank 1-3 in column 4 of table 2.1, -0.161, means that lower income rank people compare to others who are richer than them (income rank 4-7, base category and hence not shown in the table), which lowers their wellbeing. By contrast, the coefficient on income rank 8-10, 0.156, implies that richer people compare to others who are lower in the income distribution (income rank 4-7), which has a positive effect on their wellbeing. As for the interaction effects, results indicate that for high social capital people (SC=2), the negative income rank (1-3) effect -0.161 becomes $-0.161 + 0.191 = 0.03$, which in percentage terms is $0.191/0.161 = 118, 63\%$. This reads as to say that the negative effect of comparing to people higher up in the income distribution is completely offset for people who have high levels of social capital. In a similar way, for the richest people comparing to middle income people, the social comparisons effect is around 77% lower ($0.120/0.156 = 0.769$) when they have high social capital.

The last column of table 2.1 refers to the analysis of SOEP data which includes individual fixed effects. Results support the hypothesis of moderation of social capital, suggesting that socially active people are less concerned with social comparisons than others. This effect increases with social capital, so that the coefficients of income variables on life satisfaction are larger when social capital is higher.

Tables 2.2 and 2.3 show the moderation effects computed using the coefficients from Table 2.1 (please, refer to section 2.2 for details about the computation of moderation effects). Percentages in the tables indicate the share of the effect of absolute income and social comparisons on subjective wellbeing that is moderated by each level of the social capital index. Table 2.2 reports the moderating effects for all the measures of subjective wellbeing (life satisfaction, happiness, feeling depressed, job satisfaction) available in the EUSILC (first panel), European Social Survey (second panel) and the WVS-EVS (third panel, last two rows). The results consistently exhibit large moderation effects. In all of the cases, for each level of social capital the moderating role is larger for social comparisons, as measured by reference income, income rank and social class, than for absolute income. In all cases the effect of income (that is the moderation effect) is nearly 50 percent lower for people with the highest levels of social capital, while in most cases the correlation of social comparisons with subjective wellbeing is nearly off-set for people with high social capital.

Table 2.1: The role of social capital in the relationship between absolute income and social comparisons with subjective wellbeing. Regression results from four datasets.

		EU-SILC			ESS		WVS-EVS		SOEP
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Life satisfaction	Depressed	Job Sat.	Life satisfaction	Happiness	Life satisfaction	Happiness	Life satisfaction
Variables in common	Absolute income	0.511***	-0.156***	0.675***	0.529***	0.491***	0.108***	0.0179***	0.474***
		(0,019)	(0,009)	(0,042)	(0,034)	(0,046)	(0,009)	(0,003)	(0,041)
	Reference income	-0.158***	0.105***	-0.397***					-0.698***
		(0,035)	(0,018)	(0,064)					(0,145)
	Social capital index = 1 * absolute income	-0.0806***	0.0582***	-0.268***	-0.153***	-0.261***	-0.0210**	-0.00383	-0.0824**
		(0,02)	(0,010)	(0,0454)	(0,051)	(0,047)	(0,011)	(0,004)	(0,041)
	Social capital index = 2 * absolute income	-0.241***	0.0911***	-0.392***	-0.274***	-0.327***	-0.0583***	-0.00968***	-0.127***
		(0,02)	(0,009)	(0,044)	(0,054)	(-0,050)	(0,012)	(0,004)	(0,043)
	Social capital index = 3 * absolute income								-0.207***
									(0,049)
	Social capital index = 4 * absolute income								-0.248***
									(-0,063)
EU-SILC	Social capital index = 1 * reference income	0.0442**	-0.0589***	0.213***					
		(0,02)	(0,009)	(0,046)					
	Social capital index = 2 * reference income	0.148***	-0.101***	0.276***					
		(0,02)	(0,0096)	(0,055)					
European Social Survey	Income rank 1-3				-0.161**	-0.0804			
					(0,069)	(0,064)			
	Income rank 8-10				0.156**	0.105*			
					(0,062)	(0,056)			
	Social capital index = 1 * Income rank 1-3				0.0102	-0.0713			
					(0,081)	(0,073)			
	Social capital index = 1 * Income rank 8-10				-0.0665	-0.110*			
					(0,070)	(0,062)			
	Social capital index = 2 * Income rank 1-3				0.191**	0.0615			
					(0,083)	(0,075)			
	Social capital index = 2 * Income rank 8-10				-0.120*	-0.134**			
					(0,070)	(0,062)			
WVS-EVS	Social class (subjective)						-0.381***	-0.103***	
							(0,024)	(0,008)	
	Social capital index = 1 * Social class (subjective)						0.125***	0.0277***	
							(0,028)	(0,009)	
	Social capital index = 2 * Social class (subjective)						0.197***	0.0393***	
							(0,029)	(0,009)	
Socio-Economic Panel	Social capital index = 1 * reference income								0.246**
									(0,114)
	Social capital index = 2 * reference income								0.429***
									(0,121)
	Social capital index = 3 * reference income								0.466***
									(0,143)
	Social capital index = 4 * reference income								0.550***
									(0,200)
	Social capital main effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Constant	4.399***	2.612***	5.082***	3.573***	3.801***	8.071***	3.854***	9.434***
		(0.224)	(0.121)	(0.367)	(0.402)	(0.377)	(0.179)	(0.059)	(1.05)
	Number of observations	317978	317978	152095	38597	38597	48849	49973	129901
	Adjusted R^2	0.315	0.171	0.120	0.253	0.221	0.147	0.121	0.0585

Note: all regressions are estimated with OLS with robust standard errors. t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Omitted categories: "Social capital = 0", "Social capital = 0 * log of absolute income", "Social capital = 0 * log of reference income" for EU-SILC. "Social capital = 0", "Social capital = 0 * log of household income", "Social capital = 0 * income rank 4-7" for ESS. "Social capital = 0", "Social capital = 0 * household income", "Social capital = 0 * social class" for WVS-EVS. "Social capital = 0", "Social capital = 0 * log of absolute income", "Social capital = 0 * log of reference income" for SOEP.
Controls: Gender, age group, marital status, educational level, labour market status, house owner, country dummies, person has a permanent disability (EU-SILC); Gender, age, age squared, living with partner, have children, years of education, disabled, labour market status (ESS); Gender, age, age squared, education, marital status, number of children, labour market status, country and year dummies (WVS-EVS); Gender, age, age squared, marital status, years of education, labour market status, house owner, disabled, living in East Germany, regional dummies, year dummies (SOEP).
The estimated model for the SOEP is a panel OLS regression with Fixed Effects, while the other datasets are cross-sections.
A VIF test for multicollinearity of social capital shows values lower than 5 for each dataset. Detailed results are provided in the Appendix.

In other words, the subjective wellbeing of socially isolated people (social capital index = 0) depends nearly twice as much on their absolute income than the wellbeing of a socially active person (maximum level of the social capital index). As for social comparisons, the wellbeing of socially active individuals is nearly unrelated to whether the Joneses are more or less well-off. Vice-versa, social comparisons matter most to isolated individuals. These results are consistent with findings from SOEP data. The first row of table 2.3 indicates that the greater individuals' social capital, the less absolute income matters for their subjective wellbeing. The moderation effects range from -17.38% for people with low social capital to -52.32% for people with the highest level of social capital. The moderation effects are consistently larger for reference income: from -35.2% for people with low social capital, to -78.80% for people with high social capital.

SOEP data have also been used by Bárcena-Martín et al. (2017) who found that bridging social capital moderates the relationship between subjective wellbeing and social comparisons, while bonding social capital does not. As our index of social capital includes both bridging and bonding measures, we checked whether the individual dummies that compose the index match the findings by Barcena-Martin and colleagues. The results from all the datasets, including SOEP, indicate that both components of social capital moderate the wellbeing - social comparisons relationship in similar ways (see Appendix, table A.32). This discrepancy with respect to Barcena-Martin and colleagues' finding may be explained by the fact that, in the analysis of SOEP data, we use a more frequently observed measure of bonding social capital (helping friends) than the one used by Barcena-Martin and colleagues (frequency of meeting relatives and friends). An additional difference with their work is that they do not compute reference groups, but they assume that individuals compare themselves to the national income distribution, and estimate different specifications of social comparisons depending on the sensitivity of individuals to proximity. However, their measure implies the assumption that individuals have extensive knowledge of the national income distribution. Our measures of social comparisons allow us to relax this assumption as they require a more limited set of information available to the respondent.

In sum, results from the four considered datasets indicate that social capital moderates the correlation between social comparisons and subjective wellbeing. The coefficients of the remaining control variables, such as age, gender, marital and occupation status, are consistent with those found in previous literature (Dolan et al., 2008; Powdthavee, 2010; Sarracino, 2013). In particular, being female predicts higher happiness, age shows an inverted-U shape, having an illness negatively correlates with wellbeing, as do being divorced or separated and being unemployed. Being a student, retired and owning a house instead correlate positively with subjective wellbeing. We note that results are qualitatively unchanged when the health control variable is not included. The collinearity between social capital and income variables could raise some concerns about the reliability of our results. A Variance Inflation Factor test for multicollinearity shows that multicollinearity is not a concern (VIF is consistently below 5, as seen in table A.1 in the Appendix). Additionally, correlation tables between absolute income, measures of social comparisons and social capital are available for each dataset in the Appendix (please, refer to tables A.3, A.15, A.25, A.33). Coefficients indicate that the correlation between social capital and income variables should not raise particular concerns. However, to check the robustness of our results, we estimate a slightly modified version of Eq. 2.1, in which we substitute the index of social capital with its components (e.g. trust in others and the frequency of meeting friends in case of the EU-SILC). Results are robust to the different specifications. The complete set of regression results is available in Appendix (see tables A.4, A.14, A.23 and A.32). To sum up, available evidence supports the view that poor social relations boost the association between both absolute income and social comparisons, and subjective wellbeing.

Table 2.2: Moderation effects of social capital in the relationships between absolute income and social comparisons with subjective wellbeing. Results from cross-sectional data.

	Life Satisfaction		Happiness		Depressed		Job Satisfaction	
	SC index = 1	SC index = 2	SC index = 1	SC index = 2	SC index = 1	SC index = 2	SC index = 1	SC index = 2
European Union Statistics on Income and Living Conditions								
Absolute income	-15,77%***	-47,16%***			-37,3%***	-54%***	-39%***	-58%***
	(0,0334)	(0,0221)			(0,0461)	(0,0334)	(0,04542)	(0,0325)
Reference income	-27,97%***	-93,67%***			-56%***	-96%***	-53,65%***	-69,52%***
	(0,1077)	(0,1770)			(0,1025)	(0,1492)	(0,0926)	(0,1274)
European Social Survey								
Absolute income	-28,92%***	-51,8%***	-53,16%***	-66,6%***				
	(0,0766)	(0,0700)	(0,0694)	(0,0715)				
Income rank 1-3	-6%	-118,63%***	89%	-76%				
	(0,4771)	(0,3458)	(1,52)	(0,5954)				
Income rank 8-10%	-43%	-77%***	-104,7%***	-127,61%***				
	(0,3202)	(0,2430)	(0,327)	(0,3176)				
Integrated World Values Survey - European Values Study								
Absolute income	-19,44%**	-54,6%***	-21%	-50%***				
	(0,084)	(0,0669)	(0,1978)	(0,2208)				
Social Class	-32,9%***	-51,8%***	-26,59%***	-37,7%***				
	(0,058)	(0,054)	(0,0741)	(0,0681)				

Note: Moderation effects indicate by how much each level of the social capital index reduces the income coefficients of the subjective wellbeing regression.
S.e. in parenthesis are calculated with an error propagation method.
Method: OLS regression with robust standard errors of the three proxies of subjective wellbeing. Errors (in parentheses) are estimated using the error propagation method.

2.3.1 Robustness tests: the Lewbel Method of heteroskedasticity generated instruments

Since social capital may be endogenous to subjective wellbeing, we check the robustness of our findings to endogeneity bias using a Two Stage Least Square (2SLS) approach with

Table 2.3: Moderation effects of social capital in the relationships of absolute income and social comparisons with subjective wellbeing. Results from longitudinal data.

	Life Satisfaction			
	SC index = 1	SC index = 2	SC index = 3	SC index = 4
Absolute income	-17,38%**	-26,8%***	-43,6%***	-52,32%***
	(0,073)	(0,0802)	(0,0771)	(0,1129)
Reference income	-35,2%**	-61,46%***	-66,8%***	-78,80%***
	(0,1327)	(0,1743)	(0,1724)	(0,2642)

Note: Moderation effects indicate by how much each level of the social capital index reduces the income coefficients of the subjective wellbeing regression. Method: OLS regression with robust standard errors and individual fixed effects. Errors (in parentheses) are estimated using the error propagation method.

instruments generated with the method of generated instruments (Lewbel, 2012). This method is customarily used when instruments are not available. Details on this method are in section 2.2.3. We treat social capital and its interactions with social comparisons and absolute income as endogenous. We perform this analysis on all four datasets, but we run the regression uniquely on life satisfaction. This is because life satisfaction is the most commonly used proxy of subjective wellbeing in the literature, it is generally thought to be more reliable, and lastly because it is the only measure that is common and available for each of our four datasets. Results are presented in table 2.4, whereby columns 1 to 4 report the results of the analysis on EUSILC, ESS, WVS-EVS and SOEP data, respectively.

We generate the instruments according to the Lewbel (2012) method exploiting the internal structure of the data. In order for the instruments to be correctly identified they need to hold information on the variation of the endogenous variable – that is, they come from the heteroskedasticity in the model –, and should be constructed on controls that are exogenous to the dependent variable in the structural equation. Among the set of controls we choose age and age squared, as these are exogenously determined with respect to life satisfaction. A Breush-Pagan test confirms that there is heteroskedasticity in the reduced form equation of social capital with p-values consistently smaller than 0.001. In this choice of exogenous controls to construct the instruments, our approach is similar to Elsas (2021).

The first stage weak identification F statistics for the relevance of the instruments are presented at the bottom of the table. These are computed for the individual endogenous regressors. A rule of thumb indicates that an acceptable F statistics would be greater than 10 (Stock et al., 2002). Our results for the tests are in almost all cases well above the recommended threshold. This suggests that our endogenous variables are properly instrumented with non-weak instruments, except for the results estimated on the ESS dataset. Moreover, the Hansen J-statistic and the associated p-values, presented right under the

Table 2.4: Results accounting for endogeneity using two-stage least square regressions with generated instruments.

	Life Satisfaction			
	EU-SILC	ESS	WVS-EVS	SOEP
	(1)	(1)	(1)	(1)
Absolute Income	0.710***	0.920***	0.103***	1.614***
	(0.0788)	(0.170)	(0.0302)	(0.416)
Reference Income	-0.484***			-1.437***
	(0.113)			(0.255)
Income Rank 1-3		0.104		
		(0.316)		
Income Rank 8-10		-0.379		
		(0.305)		
Social Class			-0.713***	
			(0.221)	
Social capital * Absolute Income	-0.270***	-0.555***	-0.0255	-0.812***
	(0.0607)	(0.176)	(0.0280)	(0.275)
Social Capital * Reference Income	0.269***			0.656***
	(0.0832)			(0.150)
Social Capital * Income rank 1-3		-0.237		
		(0.311)		
Social Capital * Income Rank 8-10		0.460		
		(0.289)		
Social Capital * Social Class			0.427**	
			(0.212)	
Social Capital	0.821***	4.542***	-0.849	1.099
	(0.277)	(1.318)	(0.698)	(1.745)
Number of Observations	317978	38597	48849	119701
Adjusted R	0.3129	0.2434	0.1293	-0.0084
Overidentification test: Hansen Statistics	1.834	5.501	9.295	1.562
HJ P-value	0.6075	0.2396	0.1577	0.6680
First step F test: Social capital	143.07	0.68	15.44	36.98
First step F test: Social capital*absolute income	36.07	0.63	126.51	16.29
First step F test: Social capital*reference income	53.87		14.48	235.63
First step F test: Social capital*income rank 1-3		61.6		
First step F test: Social capital*income rank 8-10		112.37		
Endogeneity test p-value	0.0183	0.1679	0.4179	0.0001

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, s.e. in parentheses. Instrumented variables are the “social capital”, “social capital * income” and “social capital * reference income ”. The method is 2SLS with robust standard errors, where the employed instruments have been generated using the Lewbel method.
The social capital variable is treated as continuous to limit the number of instruments necessary for identification.
Absolute income is log of absolute income for the EU-SILC and SOEP, log of household income for ESS and household income for WVS-EVS.
Reference income is log of reference income for EU-SILC and GSOEP, income rank for ESS and self reported social class for WVS-EVS.
Controls included in each of the estimated equations are the same those included in the main OLS results.
Fixed effects are included in the SOEP.

Adjusted R^2, indicate that the null hypothesis of the instruments being valid is not rejected. However, we caution that results from the ESS and the WVS-EVS suggest that at least one variable between social capital and its interactions with absolute income and social class are not endogenous.

The coefficients from the 2SLS applied to the remaining two datasets support our previous findings: in the EUSILC and SOEP datatsets absolute income attracts a positive and significant coefficient ($b = 0.71^{***}$ and $b = 1.61^{***}$, respectively); social comparisons, measured as reference income (row 2) attracts negative and significant coefficients. The interaction between absolute income and social capital suggests that social capital reduces the association between absolute income and subjective wellbeing; importantly, the coefficient of the interaction between social capital and reference income is always positive and significant suggesting that the effects of social comparisons for subjective wellbeing are moderated by social capital.

Table 2.5 reports the results of the moderation effects. The effects are similar to those found using the OLS method shown in the previous section, for which social capital significantly moderates both absolute income and reference income in the EUSILC and SOEP datasets. The magnitude of the moderation effects after 2SLS suggest that the importance of both absolute and reference income are decreased by almost half (between 38% and 56%) for people with higher levels of social capital.

2.3.2 High social capital countries have low wellbeing inequality

To what extent are rich people happier than poorer ones? Our micro results suggest that the answer to the previous question changes on the basis of social capital: in high social capital countries the distribution of income should affect the distribution of subjective wellbeing less than in low social capital countries because absolute income and especially social comparisons matter less for the subjective wellbeing of people with rich social lives. Fig. 2.2a and Fig. 2.4a provide supporting evidence for this implication. Across 29 European countries and 99 regions the difference (gap) between the average life satisfaction of people in the richest and poorest income quintiles is smaller where the share of socially active individuals is greater. Conversely, money matters more for wellbeing in places where such shares are lower. For instance, in Serbia and Bulgaria, where social capital is very low (see the upper left corner in Fig. 2.2a), the life satisfaction gap between rich and poor people is more than 2.5 points (on a 0-10 scale), whereas in socially rich countries – such as Switzerland or Netherlands (see the lower right corner) – it is around 0.7.

Such differences could be affected by income inequality, which is greater in Serbia and Bulgaria than in Switzerland or Netherlands. As income is a well-established determinant of subjective wellbeing – as confirmed by our micro analysis – it is straightforward to expect

Table 2.5: Moderation effects computed after 2SLS.

	Life Satisfaction SC index increase			
	EU-SILC	ESS	WVS-EVS	SOEP
Absolute income	-38%***	-60%***	-25%	-50%***
	(0,043)	(0,083)	(0,195)	(0,04)
Reference income	-56%***			-46%***
	(0,055)			(0,04)
Social class			-60%	
			(0,1201)	
Income rank 1-3		-228,64%		
		(4,016)		
Income rank 8-10		-121%		
		(0,226)		

Note: Moderation effects indicate by how much an increase in social capital reduces the income coefficients of the subjective wellbeing regression. Method: 2SLS regression with robust standard errors. Standard errors are computed with the error propagation method.

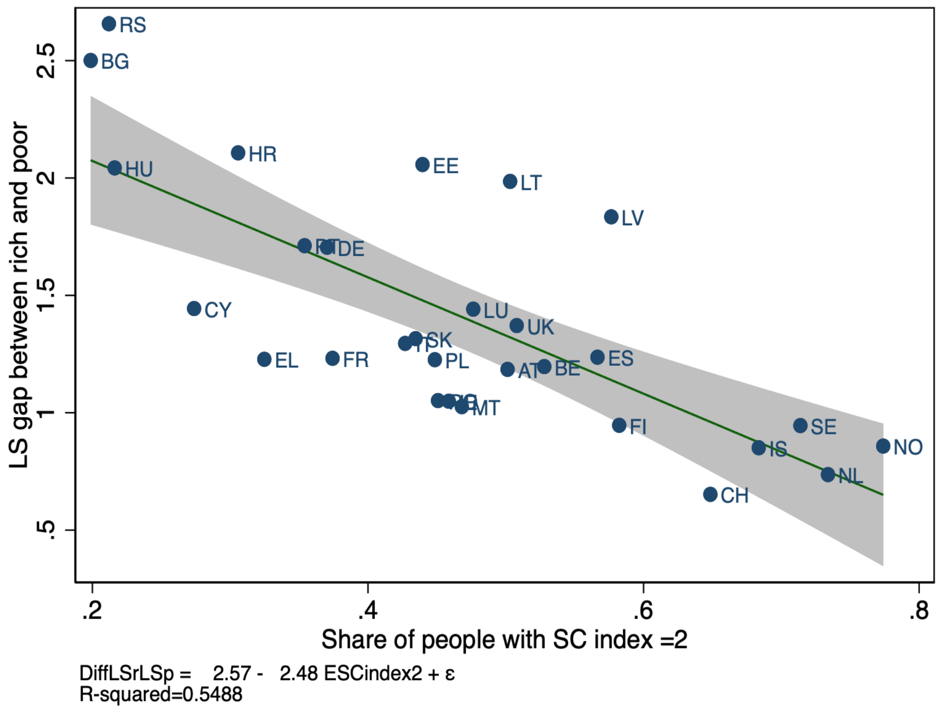

Figure 2.1: Country level - Life satisfaction gap between rich and poor people.

(a) Note: 29 European countries; data EU-SILC 2013.
Social capital is measured as the share of respondents with a social capital index = 2. The social capital index has a maximum score of 2 if a person trusts others and meets friends at least once per month. Life satisfaction ranges on a 0 to 10 scale, where largest scores stand for higher life satisfaction. Aggregated data are computed from individual data using sample weights.

that the distribution of income affects the distribution of subjective wellbeing. Moreover, a more skewed income distribution tends to exacerbate social comparisons, amplifying well-being differences between income groups. However, income inequality only partially affects such differences. As shown in table 2.6 which estimates Eq. 2.7, holding constant the Gini index of the income distribution and GDP per capita, countries and regions where social capital is higher exhibit a smaller life satisfaction gap between rich and poor people than elsewhere. As expected, we find a positive correlation between income inequality and life satisfaction gap, though significant only in the analysis carried out at the regional level of the EU-SILC data (the estimated coefficient for Gini index is 0.241 in column 1). Also GDP may affect the life satisfaction gap, as shown by Clark (2017) who finds that richer countries show lower happiness inequality. Our results mostly confirm his finding, though the effects of GDP per capita are entirely insignificant (see the last row of table 2.6). These

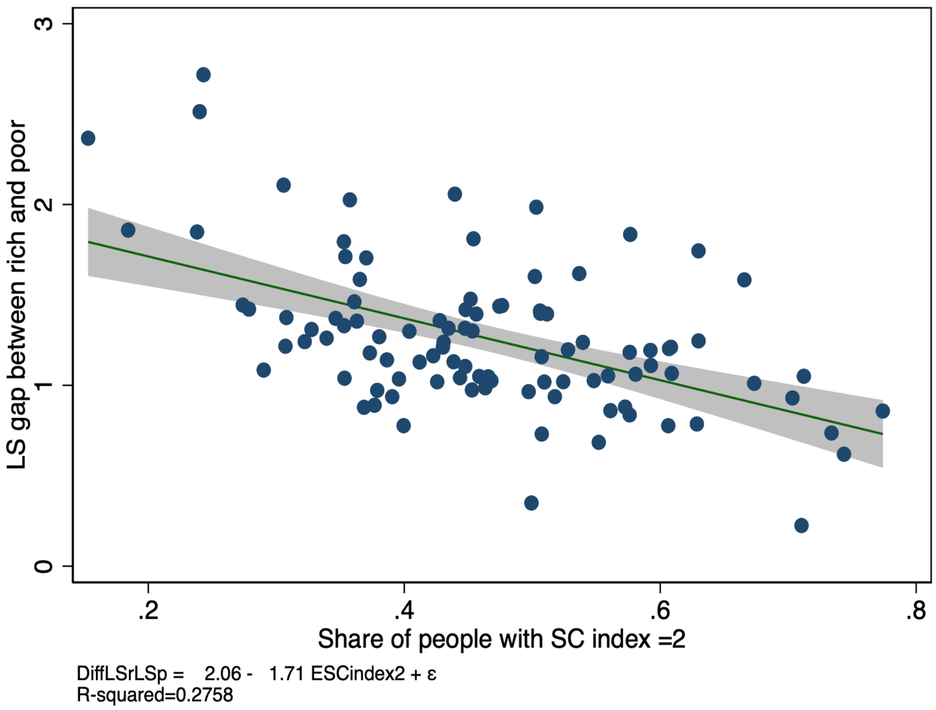

Figure 2.3: Regional level - Life satisfaction gap between rich and poor people.

(a) Note: 99 European regions; data EU-SILC 2013.
Social capital is measured as the share of respondents with a social index equal to 2. The social capital index has a maximum score of 2 if a person trusts others and meets friends at least once per month. Life satisfaction ranges on a 0 to 10 scale, where largest scores stand for higher life satisfaction. Aggregated data are computed from individual data using sample weights.

results are robust to alternative measures of inequality, such as the 90/10 and 50/10 income inequality ratios (results are available in tables A.9, A.11, A.10, A.12, A.20, A.21 and A.30 in the Appendix): all other things being equal, the higher the share of individuals with high social capital, the lower the life satisfaction gap between the rich and the poor.

In conclusion, after controlling for the Gini index of income and GDP per-capita, the life satisfaction gap between rich and poor people is smaller in countries and regions with high social capital than elsewhere (see the coefficients in the first row of table 2.6). This cross-country/region results reflect the micro-level findings presented previously. The more income matters for wellbeing, the more income disparities translate into subjective wellbeing disparities between income groups. In countries with high social capital, money matters less for subjective wellbeing, and the life satisfaction gap between income groups is relatively small. This result is driven by the moderating effect of social capital, which is stronger for social comparisons than for absolute income.

Table 2.6: Life satisfaction gap and social capital controlling for the Gini index of income and GDP per-capita.

	Life Satisfaction gap between rich and poor			
	(1)	(2)	(3)	(4)
	EU-SILC Region	EU-SILC country	WVS-EVS	ESS
Share of people with social capital index = 2	-0.498***	-0.502**	-0.149	-0.286
	(-4.95)	(-3.14)	(-1.54)	(-0.133)
Gini index	0.241*	0.291	0.00153	0.203
	(2.15)	(1.95)	(0.01)	(1.48)
GDP per capita (log)	0.0191	-0.109	-0.0391	-0.327
	(0.27)	(-0.85)	(-0.12)	(-1.35)
N	99	29	60	29

Note: t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The unit of analysis are countries (except in Column 1, in which the unit of analysis are regions).
The dependent variable is the difference in average subjective wellbeing, as measured using life satisfaction, between the first and fifth income quantile in a given country.
All coefficients are standardised for comparability. The regression using WVS-EVS data includes time fixed effects to account for the fact that some countries are observed multiple times. The sample available for the regression is N = 60 because some of the countries have been observed more than once.
Aggregated figures are captured from individual data using sample weights.
Method: OLS regression with robust standard errors.

2.4 Discussion: redistribution and policies for social capital

Our finding has three implications. First, results support the view that people's tendency to compare their achievements to those of relevant others, i.e. social comparisons, is stronger for individuals with scarce social relations. This result supports the view of positive psychologists according to whom the race for position and the poverty of social relationships are intertwined. Consistently, previous studies documented that declining social capital coexisted over decades with increasing social comparisons in countries where economic growth was accompanied by decreasing subjective wellbeing, such as China and the US (Bartolini and Sarracino, 2015; Putnam et al., 2000; Blanchflower and Oswald, 2004).

The second implication concerns the origin of social comparisons. Some studies suggest that social comparisons are rooted in human evolution and in the biology of the brain Schmitt et al. (2016); Hopper et al. (2014); Fliessbach et al. (2007). Our result indicates that this may not be the whole story: the social context affects the importance of social comparisons for subjective well-being, especially when we use income-based measures of social comparisons. Previous studies also documented that social comparisons can negatively affect people's physical (Subramanyam et al., 2009; Pickett and Wilkinson, 2010; Hawkley et al., 2003) and mental health (Pickett and Wilkinson, 2010; Mujcic and Oswald, 2018; Gold, 1996; Smith et al., 1999), and their economic decisions (Hirsch, 1976; Neumark and Postlewaite, 1998; Bowles and Park, 2005; Layard, 2006). Our finding suggests that promoting social capital could mitigate the negative consequences of social comparisons.

The third implication of our finding is that social capital changes the extent to which income inequality affects subjective well-being inequality. The more closely income and subjective well-being are connected, the more a given income inequality should produce subjective well-being inequality.

In our micro-regressions the moderating impact of social capital on the relationship between absolute income and subjective wellbeing is never complete, suggesting that the income distribution shapes the wellbeing distribution even in the presence of high levels of social capital, although to a lesser extent. This is reflected by our macro results, which show that social capital reduces the impact of income differences on subjective differences, but does not cancel them out. In countries with high social capital, the wellbeing gap between rich and poor is greatly reduced compared to those with poor social capital, but still remains substantial. In sum, both our micro and macro results suggest that income inequality, and thus redistribution, matters independently of social capital in determining wellbeing inequality. More importantly, income inequality boosts social comparisons regardless of social capital (Cheung and Lucas, 2016; Kondo et al., 2008; Wilkinson and Pickett, 2009). Furthermore, high inequality hampers social capital (Alesina and La Ferrara, 2002; Bjørnskov, 2006; Costa and Kahn, 2003; Knack and Keefer, 1997). In sum, highly uneven societies tend to exhibit poor social capital and strong social comparisons. Thus redistributive policies have a crucial role because limited inequality is a prerequisite for a society capable of expanding the wellbeing of its members. Hence, policies for social capital may complement income redistribution, moderating the impact of income inequality on the distribution of subjective wellbeing.

Finally, we emphasize that social comparisons are the main factor driving the disappointing impact of economic growth on subjective wellbeing (Easterlin, 1974; Easterlin et al., 2010). Therefore, loosening social comparisons would allow growth to unfold its potential to increase subjective wellbeing. We suggest that a key to weaken social comparisons is to promote social capital, as well as to reduce the inequality that amplifies social comparisons. This view is consistent with previous evidence showing that economic growth correlates with increasing subjective wellbeing over time when social trust does not decline and income inequality does not increase (Mikucka et al., 2017).

If social capital is important, how can it be promoted? Domains such as urban planning, education, and advertising devoted considerable attention to policies for social capital. In particular, according to New Urbanism, an urban design movement, planning cities and neighborhoods with high residential density, walkability, pedestrian areas, parks, car restrictions and public transport can contrast the effects of car-oriented urban development. Re-organizing common spaces and transport is thus critical to relieve the urban car-dependency, and promoting social capital (Montgomery, 2013). Long commutes take a high relational toll: people who spend more than 45 minutes commuting are less happy than others, and they are 40 percent more likely to divorce (Olsson et al., 2013). Studies comparing traditional high-density neighborhoods and conventional low-density suburbs find greater social interaction and sense of community in traditional neighborhoods, and availability of pedestrian areas increased the likelihood of social interactions (Kim and Kaplan, 2004; Lund, 2003). Other studies focus directly on the degree of walkability (Frank et al., 2010) and demonstrate that more walkable neighborhoods enhance social interactions and a greater sense of community (Leyden, 2003; Lund, 2003; Du Toit et al., 2007; Wood and Christian, 2011; Rogers et al., 2011, 2013; Alesina and La Ferrara, 2002). Gilderbloom et al. (2015) have shown that walkability has a positive impact not only on neighborhoods' social fabric, but on real estate prices, foreclosures and even crime rates. Walkable neighborhoods translate into more "eyes on the street", which leads to less crime.

Evidence from education studies shows that children's education heavily affects the development of the social skills that are critical for the development of social capital later in life. Current teaching practices, mostly based on vertical teaching, contribute to make education a distressing and competitive experience for most students (OECD, 2017). Participatory teaching practices are an effective alternative. Participatory teaching is based on students' group work on common projects, in student-centered classrooms and has been shown to foster students' social capital in the forms of cooperation with other students and teachers, membership in associations, trust in institutions, and participation in civil society (Algan et al., 2013). Predictably, more cooperation-oriented schooling practices shape more cooperative individuals. The foundations of participatory teaching were laid by Montessori education – a century-old schooling method (Biswas-Diener, 2011). Lillard and Else-Quest (2006) found that Montessori education fosters social and academic skills more than traditional education.

Lastly, advertising negatively affects social capital and increases social comparisons, especially for children and teenagers. Studies have documented a relationship between exposure to advertising and materialism in children (Schor, 2004; Goldberg and Gorn, 1978; Pollay, 1986; Buijzen and Valkenburg, 2003; Nairn et al., 2007). By triggering feelings of exclusion in those who do not buy the advertised products (Schor, 2004), advertising promotes social comparisons. Similar to adults, children's materialism is bad for their social capital: it is associated with family conflict, less generosity and more anti-social behaviour

(Cohen and Cohen, 1996; Kasser and Ryan, 1993; Buijzen and Valkenburg, 2003; Nairn et al., 2007; Kasser, 2005). Increasing awareness of the damage caused by commercial pressure has lead various Western countries to regulate advertising. Norway and Greece banned television advertisements targeting kids, New Zealand prohibits advertising of junk food and Austria and Belgium have banned ads targeting kids before, during or after children's TV programs. Authorities for the regulation of advertising are at the forefront in regulating children's media in countries such as Australia, Canada, and the UK (Lisosky, 2001; Caron and Hwang, 2014). Advertising fosters social comparisons among adults as well; thus, regulating advertising would benefit adults too.

2.5 Conclusion

In this paper we show that social capital has a powerful moderating effect on the relationship between social comparisons and subjective wellbeing. First, we observed that social comparisons impact the wellbeing of those who have a rich social life less than isolated people. Furthermore we have documented that social comparisons become less important to subjective the wellbeing of individuals when their social capital increases over time. Finally, comparing different countries, we observe that income is less important for the wellbeing of citizens of countries where the social fabric is stronger.

While the moderation of social capital on social comparisons shows a similar pattern in all our regressions, absolute income does not exhibit clear-cut results. Non-instrumented regressions show that the moderation effect is smaller for absolute than for reference income, yet it is sizeable and increasing in social capital. However, the coefficient of the interaction between social capital and absolute income in the instrumented regressions is statistically significant only in EU-SILC data. All in all, these results suggest that absolute income is likely to be an important correlate of wellbeing whatever the level of social capital. In other words, high levels of social capital considerably weaken the relationship of wellbeing with social comparisons while the income/wellbeing relationship remains substantial.

The empirical approach used in this study has some limitations. First, statistical identification of a causal relation is challenging. As it is often the case, exogenous sources of variation are scarce and it is difficult to identify the direction of causality. However, the individual-based evidence is reassuring: the results obtained using the method of generated instruments lend some support to a causal interpretation of our findings. A second limitation relates to the use of large samples, which comes at the expense of not having a rich battery of questions to measure social capital.

Despite these limitations, our evidence on the moderating effect of social capital on the relationship between social comparisons and subjective wellbeing is extensive, as it concerns a variety of countries, measures, wordings of the variables of interest, types of income (absolute and relative) and forms of social capital (bridging and bonding). These results provide encouraging news about the possibility of increasing subjective wellbeing. People are not doomed to play the zero-sum game of social comparisons: promoting social capital may be an effective strategy to minimize the negative impact of social comparisons on subjective wellbeing. As social comparisons are the main reason for the disappointing impact of economic growth on subjective wellbeing, social capital appears to allow growth to fully display its potential to increase subjective wellbeing. Social capital has been shown to promote happiness, health, social cohesion, resilience and economic prosperity. According to our findings, the list of the beneficial effects of social capital should include also the moderation of social comparison.

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Chapter 3

The wellbeing effects of social capital in times of a health crisis: the case of the Covid-19 pandemic

Abstract

In this paper I analyse the sheltering effect of social capital in the relationship between the pandemic and people's levels of mental distress and life satisfaction. I present a theoretical description of the mechanisms by which social capital influences wellbeing, which I adapt to the context of a health crisis. I test two hypotheses using monthly panel data from the UKHLS: first, that the wellbeing of people with high pre-pandemic levels of social capital decreased more than the wellbeing of others with respect to their pre-pandemic levels; second, whether social capital allowed people to face the pandemic better, with higher levels of subjective wellbeing on average. The results confirm both hypotheses and are robust to a number of model specifications, as well as tests for possible endogeneity between social capital and wellbeing. The findings show that, first, high social capital individuals experienced greater decreases in wellbeing when compared to their pre-pandemic levels, and second, high social capital people have better mental health and higher life satisfaction than low social capital people throughout the period.

Keywords: *Subjective wellbeing; General Health Questionnaire; life satisfaction; social capital; UKHLS*

3.1 Introduction

The Covid-19 pandemic has been an unprecedented event in recent history, with massive implications on the economy, health and wellbeing. In the UK, economic activity fell by far, health costs became extremely high (Niedzwiedz et al., 2021; Banks and Xu, 2020; Pierce et al., 2020) and the incidence of psychological distress and mental health related issues spiked (Pierce et al., 2020). Psychological and health-related outcomes have been significantly affected by the risk of getting the virus, and the policies adopted by the government to prevent its spread. Lockdown measures that limited people's movements have been found to affect individuals' mental health and wellbeing (Kwong et al., 2021). Studies that have assessed mental health trends since the beginning of the pandemic have reported increased symptoms of anxiety disorder, depression and loneliness starting in April and May 2020 (Fancourt et al., 2021; Bu et al., 2020). Common risk factors for mental health deterioration that have been reported include being a woman, young and having chronic physical or mental illnesses and being unemployed (Proto and Quintana-Domeque, 2021; Niedzwiedz et al., 2021; Gagné et al., 2021; Pierce et al., 2020). Most of these factors were already associated with being at risk of lower levels of mental health before the pandemic, and the pandemic exacerbated this probability.

The aim of this study is to understand the role of social capital in the relationship between the Covid-19 crisis and subjective wellbeing in the UK. Specifically I check whether social capital sheltered individuals' against the crisis. This paper contributes to the literature on the relationship between social capital and subjective wellbeing in two ways. Firstly, I provide a theoretical description of the possible mechanisms through which social capital affects wellbeing. Secondly, I exploit the Covid-19 crisis in the setting of a *quasi*-experimental approach to analyse whether different levels of social capital changed the relationship between the crisis and individuals' wellbeing. The paper investigates this relationship using four different measures of social capital, to shed light on what social capital component matters the most as sheltering factor for wellbeing.

Social capital, in form of individuals' social relationships and participation in community networks, has been found to positively relate to subjective wellbeing and quality of life in studies conducted before the pandemic. Psychologists have since long highlighted the importance of individuals' social dimension and the role of social relationships on subjective wellbeing (Diener et al., 1999; Kahneman et al., 1999). Literature suggests that social relationships are one of the most important correlates of life satisfaction and happiness (Bartolini et al., 2013; Bruni and Stanca, 2008; Becchetti et al., 2008; Tella et al., 2003; Helliwell, 2003; Frey and Stutzer, 2002). Similar findings are also true for the public and civic characteristics of social relationships, such as trust and social engagement (Gui and Sugden, 2005; Uhlaner, 1989). Fewer studies have been conducted on the relationship between social capital and mental health. These confirm the importance of community perception, social ties and social engagement as strong factors in building resilience to adverse life events. Flores an co-authors, as an example, find that social capital lowers the risk of mental disorders while increasing resilience capacity, adaptation and recovery (Flores et al., 2018).

The spread of the pandemic offers an opportunity to investigate the relationship between social capital and subjective wellbeing in times of crisis. The strict lockdown periods and restrictions to face-to-face interactions impacted the social lives of individuals by limiting their social activities. This likely decreased the wellbeing of those who attach more importance to social interactions than others, ultimately placing social capital among the risk factors for increased mental distress and decreased life satisfaction. However, social capital may have served as protective factor that allowed people to fare better, essentially buffering the negative consequences of the pandemic on wellbeing, and contributing to wellbeing resilience (i.e. the ability of individuals to maintain their wellbeing levels during and after adverse life events, and to cope with such stressors). In the following, I test two hypotheses: firstly, that the wellbeing of people with higher social capital decreased more than the wellbeing of others compared to pre-pandemic periods; secondly, I test whether social capital still allowed to face the pandemic better, with higher levels of subjective wellbeing on average. The idea behind these hypotheses is that social capital, referred to as the social networks and values and social support that arise from interpersonal relations, operates for wellbeing in two ways. On the one hand, the positive effect of social networks comes from daily in-person interactions with other people. On the other hand, social support serves as a buffer against adversities, making social capital a protective factor against negative life events. In section 3.2.1 I formalise the operating mechanisms from social capital to wellbeing by referring to the few other studies that previously defined such mechanism, and I adapt them to the Covid-19 crisis to examine the effects of social capital for wellbeing in this setting.

Results show that people who care for their social interactions more suffered the effects of the pandemic to a higher degree than those with low levels of social capital. This confirms the first hypothesis. However, the findings also suggest that the decrease in subjective wellbeing of people with high social capital was not so high as to eliminate the positive effect that social capital usually has for wellbeing. Compared to people with low social capital, those with high social capital show on average higher wellbeing in almost each pandemic period. These results suggest that having social capital, especially certain components of it, has a protective effect on wellbeing, and that it is a factor that contributes to wellbeing resilience, confirming the second hypothesis as well. These findings are especially noteworthy because the pandemic's extreme setting of exogenous deprivation of social interactions, at least in some periods, highlights the value that social capital has for people even when they are unable to enjoy it. One might expect this deprivation to have a major negative effect on wellbeing, but this was not the case. The findings of this paper contribute to recognizing the importance of social capital in times of crisis.

Alongside the main wellbeing literature (Graham, 2011; Kahneman and Deaton, 2010; Ryan and Deci, 2001; Kahneman et al., 1999) and recent studies conducted on the effects of Covid in UK (Bonomi Bezzo et al., 2021), I consider two different wellbeing dimensions, subjective mental health and life satisfaction. A detailed description of these dimensions is reported in the data section (3.3.1). The next section defines the concept of social capital, illustrates its components and explains how it operates for wellbeing, and formalises the hypotheses of the paper. The data section (3.3.1) provides a detailed description of the utilised proxies for social capital, as well as those for subjective wellbeing. Importantly, in this study social capital is fixed and measured in a pre-pandemic period for each individual, hence it is unaffected by the crisis. This reduces the bias deriving from the endogeneity of social capital with respect to wellbeing. Then, in a similar way to a prospective study, the analysis relates to the post-pandemic subjective wellbeing trends of people who are endowed with low vs high social capital. I detail the econometric model in section 3.3.3, and present the results in section 3.4. The last two sections conclude.

3.2 On Social Capital: definition, composition and mechanisms

The literature on social capital has been growing substantially in the past few decades. Social scientists from different fields have increasingly devoted their attention to this notion, which however still lacks of a unique and comprehensive definition. Generally speaking, social capital is a concept used to describe several interrelated and overlapping phenomena that are associated with individuals' relationships to resources and people around them. According to Putnam, interpersonal relations provide benefits which create value for the people who are connected, and for the bystanders as well (Putnam et al., 2001, 2000; Putnam, 1995). Social capital is defined as the social networks and norms of reciprocity and trustworthiness arising from interpersonal relations that create value for individuals and communities: these networks and norms allow and facilitate the transmission of information and they help to overcome collective actions dilemmas. In short, as reported in the 2001 OECD report, social capital refers to the social networks, shared norms and norms of reciprocity that create value and understandings that facilitate cooperation within and among groups (Healy and Côté, 2001).

The OECD proposed four distinct components of social capital which are now widely recognised in the social capital literature (Scrivens and Smith, 2013). The components are defined as follows:

1. *Personal relationships*, which refer to the structure of the people's networks (i.e. the people they know) and the behaviours that contribute to establishing and maintaining those networks.

2. *Social network support*, which refers to the outcome of the nature of people's rela-

tionships and to the resources that are available to each person as a consequence of their personal social networks. These resources may be emotional, material, practical or even financial and intellectual.

3. *Civic engagement*, which comprises the activities and networks through which people contribute to civic and community life, such as volunteering, political participation, group membership and different forms of community action.

4. *Trust and cooperative norms*, referring to the trust, social norms and shared values that underpin societal functioning and enable mutually beneficial cooperation. The concept pertains different kinds of trust, as well as norms of reciprocity and non-discrimination. The types of trust that are most often considered as forms of social capital are generalised trust (i.e. trust in 'others', including strangers) and institutional trust, such as trust in political institutions, police, the media or other institutions.

The Office for National Statistics in UK adopts the same definition and categorisation for social capital as the OECD. They refer to social capital as a term used to describe the extent and nature of the connections with others and the collective attitudes and behaviours between people that support a well-functioning, close-knit society (Office for National Statistics, 2020). In the following, I perform a principal component analysis on UK data and retain four components that closely mimic the OECD and ONS definition. These components are then used to analyse their effects on the wellbeing trends throughout the pandemic period.

Berkman et al. (2000) are among the few authors who define a theoretical model of how social networks relate to health and mental health outcomes using an interdisciplinary approach. They argue that social networks operate at a behavioural level (on health) via the provision of social support, and engagement and participation, among other pathways. Importantly for this context, their definition of social networks resembles that of social capital in this paper. They define social networks as "the web of social relationships that surround an individual and the characteristics of those ties" (Berkman et al., 2000, pg.847) and describe the structure and the characteristics of such networks. Following Weiss (1974), they argue that social support includes emotional and instrumental support, and relates to the love, caring and understanding available from others. It additionally relates to the help and assistance with tangible needs that require physical interactions. Participation and engagement instead result from the enactment of potential ties in real life activity such as getting together with friends, attending social functions, participating in occupational or social roles, group recreation and church attendance, which are all instances of social engagement. The way social networks ultimately affect health, and mental health, in their model is via providing opportunities for social support, social engagement and participation that in turn produce a sense of belonging, attachment, companionship and sociability which are related to positive health outcomes and behaviours[1]. More recently, Hoogerbrugge and Burger (2018) offer another example of the operationalization of social capital for wellbeing. They discuss that neighbourhood social capital operates for life satisfaction via social contacts with neighbours or via perceived social cohesion within a neighbourhood.

3.2.1 Hypotheses

Both the studies from Berkman et al. (2000) and Hoogerbrugge and Burger (2018) suggest that there are at least two ways through which social capital can affect subjective wellbeing, that are, loosely speaking, real life (in person) social interactions, and perceived cohesion, belongingness and support. The framework for this paper builds and adapts on Berkman et al. (2000), and exploits the definition of social capital as *interpersonal relationship and networks*, and the *values* that come from them, to explain the double effect it had on subjective wellbeing during the Covid period. The underlying hypothesis is that social capital, via participation and engagement, provides a sense of belonging, attachment, companionship and sociability that customarily relate to higher wellbeing. Then the positive effect of social capital for wellbeing may stem from either the daily interactions with people in the network, or from what remains of the interactions, which is the value of having such networks. More specifically, on the one hand the wellbeing benefits of social capital, in the forms of social interactions and networks, are observable when people engage in social activities everyday, by interacting with friends and family or with the community around them. On the other hand however, social capital could entail higher wellbeing by leaving intrinsic values within people as a result of having engaged with their social networks. Such values have been built over time as a result of the repeated social interactions, and remain within the person even when they are unable to enjoy in-person social activities. The values include sense of belonging, attachment, social cohesion, trust and reciprocity that create a base for sustained wellbeing and wellbeing resilience in times of crisis.

The two motivating hypothesis for this paper then build on the double operating mechanism of social capital for wellbeing, by adapting it to the health crisis setting of the Coronavirus pandemic. In particular, the hypotheses are the following:

1. People with higher social capital suffered a larger deterioration of their wellbeing with respect to their pre-pandemic levels than others. Mandatory isolation policies and the lack of face to face interaction affected the wellbeing of people who care for social interactions more than people who do not customarily value social capital as much. Essentially, having high social capital exacerbated the already negative effects of the pandemic for subjective wellbeing. This hypothesis relates to the importance of

[1]For a detailed description of how each pathway looks in their model, please refer to section *Downstream social and behavioural pathways* of their paper.

frequent in person social interactions, and to the fact that an exogenous-like limitation to such interactions weighs more on the wellbeing of those for whom social capital is important.

2. Compared to people with low social capital, the subjective wellbeing of people with more social capital decreased less during the pandemic. If the first hypothesis held, it is possible that high social capital individuals suffered so much that the positive effect of social capital for wellbeing has been offset, making them ultimately worse off compared to low social capital people. However, I hypothesise that, consistently with Cohen and Wills (1985)'s framework of coping mechanisms in times of stress, the values and feelings of cohesion and belonging that stem from interpersonal relationships remain within the person allowing for wellbeing resilience and to fare better even in times of isolation and distress.

3.3 Data and Methods

3.3.1 Data

Data come from the Understanding Society - UK Household Longitudinal Study (UKHLS). It is a nationally representative panel survey based on a stratified random sample of the population. The current analysis is undertaken on a merged dataset built on data from the yearly main survey (University of Essex, Institute for Social and Economic Research, 2022) and the Covid-19 special release survey (University of Essex, Institute for Social and Economic Research, 2021) conducted by the Institute for Social and Economic Research. The first observation period comes from the years 2017-2019 (wave 9) of the main survey of UKHLS, while the remaining nine periods come from the special Covid release. Since April 2020 participants from the main sample have been invited to complete short web-surveys which cover the impact of the pandemic on the welfare of UK individuals and families. Participants completed a regular survey, which includes core content designed to track changes, alongside variable content adapted as the coronavirus situation developed.

The Covid-19 study was conducted monthly until July 2020, then bimonthly until March 2021 with an additional survey in September 2021. The employed dataset uses ten time periods in total where the first time period contains data collected between 2017 and 2019 and the remaining nine are data collected for the months of April, May, June, July, September, November 2020 and January, March and September 2021. The panel is unbalanced and the number of individuals is 6870, for a total of 48148 individual-time observations. Individuals retained in the sample are those who have non missing values on the wellbeing questions. Since one of social capital components, *trust and cooperative norms*, was measured last in 2015, the sample is further reduced to those who have not changed their address since the interview year in which they answered that social capital question. The question pertains the neighbourhood perceptions and for it to have meaning for current wellbeing it should be the same neighbourhood they have lived in since. In a robustness check, I perform the same estimation procedure to the unrestricted sample, without the inclusion of the *trust and cooperative norms* component, and results are qualitatively the same.

3.3.2 Measures

The outcome variables for this study are two different dimensions of subjective wellbeing, self-reported mental health (measured as distress) and life satisfaction. Mental health is the result of positive and negative feelings derived from day to day conditions and experiences, and it is proxied with a psychiatric measure of the General Health Questionnaire. Evaluative wellbeing is the result of the evaluation of one's own life overall and is proxied with life satisfaction (Pavot and Diener, 1993; Bonomi Bezzo et al., 2021). While related, it is important to separately analyse them both from an empirical and theoretical standpoint (Krueger and Stone, 2014).

The GHQ variable. The first outcome variable is subjective mental health and it is measured using the General Health Questionnaires (GHQ) which was included in both the UKHLS main survey and in the special Covid-19 survey release. The GHQ is a well-known self-reported and commonly used instrument for evaluating the mental health of the respondent where she must report the extent to which some symptoms were present in the past few weeks (Goldberg et al., 1997). The GHQ variable is a measure that converts valid answers to the 12 questions of the General Health Questionnaire to a single scale by recoding so that the scale for individual variables runs from 0 to 3 instead of 1 to 4, and then summing, giving a scale running from 0 (the least distressed) to 36 (the most distressed). Appendix 1 lists the detailed composition of the questionnaire, with the 12 questions and the four possible answers to each of them. It has been in many cases used as a screening device to detect psychiatric cases or to estimate the prevalence of psychiatric disorder within samples (Winefield et al., 1988; Hepworth, 1980; Finlay-Jones and Eckhardt, 1981). It may also be used to estimate the percentage of population with a high score on the GHQ, hence to estimate the prevalence for psychiatric disorders in the population and lastly to measure change in mental state following distressing events like accidents, injuries or catastrophes. This measure was originally developed as a self-administered screening tool designed to detect current mental disturbances and disorders and it has been deemed the best measure validated among similar screening tools, in a wide range of samples and in a variety of social and cultural settings (Winefield et al., 1988; Tennant, 1977).

Life satisfaction. The second outcome variable is life satisfaction. Life satisfaction is generally defined as an overall appreciation of life as a whole (Veenhoven, 1984, 2000; Pavot and Diener, 1993) and regarded as one of the components of subjective wellbeing because this concept includes people's emotional responses, domain satisfaction and global judgements of life satisfaction (Diener et al., 1999). The question asked in the survey is "Here are some questions about how you feel about your life. Please choose the number which you feel best describes how dissatisfied or satisfied you are with the following aspects of your current situation: your life overall". Answers range from 1 to 7, 1 being completely dissatisfied and 7 being completely satisfied.

Social capital. The Understanding Society data provides multiple variables that may be used as proxies for social capital, including reliance on friends, active participation in associational groups and neighbourhood cohesion measures. The full list of variables selected for the current analysis, with the wording of the questions and scales of answers is reported in table B.2 in the appendix. Since the original variables are on different scales, they are all dichotomised for homogeneity. The rule is to assign value 1 to individuals whose response to each social capital question was higher than the median respondent's one, else 0, such that a value 1 indicates the individual has high social capital. I use a principal component analysis on the dummies to reduce dimensionality on the concept of social capital[2]. The analysis suggests there is no unique component contributing to the latent definition of social capital, but rather that the variables may be aggregated in four components. Tables 3.1 and 3.2 report the factor correlations and the sorting of the variables in the four components and the factor loadings.

Table 3.1: Factor analysis/correlation

Factor	Variance	Difference	Proportion	Cumulative
Factor1	1.67370	0.01194	0.1860	0.1860
Factor2	1.66176	0.13884	0.1846	0.3706
Factor3	1.52292	0.33238	0.1692	0.5398
Factor4	1.19055	.	0.1323	0.6721

Method: principal-component factor. N=20396

After PCA analysis, selecting the variables that have a factor loading larger than 0.5 and aggregating the variables that are retained in each factor, the four components of social capital are:

- *Social network support* (factor 2 of the table) proxied by the variables: being able to rely on and open up to friends. According to the above mentioned ONS definition, social network support refers to the *outcome* of having interactions with personal social

[2] This is done with Stata command *factor, pcf* which performs a factor analysis with principal component analysis (PCA) for factor extraction. This procedure assumes that there are a number of independent factors to the latent concept of social capital, and groups information in combinations of the original variables using PCA.

Table 3.2: Rotated factor loadings (pattern matrix) and unique variances

Variables	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**	**Uniqueness**
Religious group				0.7173	0.4777
Volunteer group				0.7102	0.4922
Scouts group					0.8221
Rely on friends		0.9064			0.1711
Open up to friends		0.9111			0.1679
Belongs to neighbourhood			0.8612		0.2404
Talks to neighbours			0.8564		0.2440
Can get help from neighbours	0.9012				0.1696
Trusts neighbours	0.9071				0.1661

Blanks represent abs(loading)<.5. Uniqueness is the same as "Unexplained Variance" in PCA notation.

networks. Outcome in this context is intended both as the behavioural consequences of having friends, seeing and talking to them, but also to the residual value of having created a meaningful relationship with them. In this sense, social support can be seen as a relational good (Gui, 2000; Uhlaner, 1989; Bartolini and Bilancini, 2010). These goods refer to sociability, or the quantity and quality of social relationships. Social interactions with friends entail the production and consumption of relational activities for the people who are involved. These activities include companionship, communication, emotion sharing, psychological support and solidarity and approval and have been found to typically have positive effects for wellbeing (Bartolini and Bilancini, 2010). In the context of the current analysis, the hypotheses associated to the effects of *social network support* on wellbeing will go 1) through the lack of possibility of enjoying these networks with in person interactions due to the Covid-19 containment policies, and 2) via the residual value of having already engaged with the social networks. Indeed, having understanding friends and on which one can count on is valuable to people even when they are not able to see them because of the relatedness and support on which they are built, which remains within a person and can create wellbeing resilience.

- *Personal relations* (factor 3): proxied by the variables of frequency of talking to neighbours and the feeling of belonging to neighbourhood. Engaging in social interactions with neighbours builds the necessary trust which is the foundation for the feelings of belonging and participation. Findings in the social and epidemiological literature suggest that feelings of belonging to the neighbourhood have a positive effect on both mental health and wellbeing (Elliott et al., 2014; Young et al., 2004). The main pathways feeding this relationship are social participation, availability of social support, identity and collective efficacy. With respect to the effects this component may have on wellbeing during the Covid crisis, the double effect may come, on the one side, from the lack of interpersonal interactions with neighbours during the physical isolation periods, and on the other hand, by the feelings of psychological support and identity that the neighbourhood leaves people with, that are positively correlated with wellbeing.

- *Civic participation* (factor 4): proxied by the active participation in Putnam groups (volunteer, religious and scout groups) variables. This component is built with the same variables as in Geraci et al. (2022). Putnam-type organisations were credited by Putnam et al. (1992) with the ability to instil habits of cooperation, solidarity, and public-spiritedness in their members. Knack and Keefer (1997) defined Putnam groups as those that are "least likely to act as distributional coalitions but which involve social interactions that can build trust and cooperative habits". Bartolini et al. (2013) argue that Putnam type groups are a component of social capital that has to do with intrinsically motivated social connections. The concept of intrinsic motivation refers to incentives that come from within the individual. According to Deci (1971), "one is said to be intrinsically motivated to perform an activity when one receives no apparent reward except the activity itself". Then, being a member of Putnam type groups is supposedly motivated by the pleasure of being a member in such groups, derived by acting together with individuals who share the same values and beliefs, and by the pleasure of interacting with them (Bartolini et al., 2013). In the current context, this component also works both via social contacts (or the lack thereof) and by the residual feelings of relatedness and cohesion.

- *Trust and cooperative norms* (factor 1): proxied by the trust in and possibility of getting help from neighbours variables. Trust in others or in neighbours is one of the most commonly used proxies for social capital, and has repeatedly been found to positively relate to wellbeing (Helliwell and Wang, 2010; Helliwell et al., 2016; Bartolini et al., 2017). The double effect of *Trust and cooperative norms* for wellbeing in the context of the Covid-19 crisis is also clear from how it is constructed. Being able to get help from neighbours accounts for social contacts, while the feeling like people in the area can be trusted makes for a more cognitive component, that of social cohesion, which is available to individuals even when not able to enjoy the physical interactions.

Each component is a dummy created out of the individual's average of the two (or three) dummies retained in each component from the principal component analysis, using the median value as cut-off point: individuals who have a higher value than the median are assigned 1, else 0, indicating high or low social capital. The Cronbach's alpha statistics of the reliability of the sorting of variables in each component are larger than 0.7 (except for the civic participation component, with an alpha of 0.2, but whose reliability is given by external validity), indicating a good sorting of the variables in the factors. These components closely resemble those suggested by the OECD and by the UK Office for National Statistics, which gives external validation for the use of different components of social capital. Moreover, the advantage of keeping the proxies separate is that the effects of each factor are detected individually, shedding light on what matters the most for subjective wellbeing.

3.3.3 Empirical Model

In order to assess the role of social capital in the relationship between the Covid-19 crisis and wellbeing I perform a panel regression analysis with random effects. The estimated equation takes the following form:

$$Wellbeing_{it} = \alpha + \beta_1 Covid_t + \beta_2 SC_i + \beta_3 Covid_t * SC_i + \beta_4 X_i + \beta_5 X_{it} + \beta_6 \bar{X}_i + \epsilon_{i,t} \quad (3.1)$$

where $wellbeing_{it}$ is proxied by self reported mental distress (the GHQ variable) and life satisfaction; $Covid_t$ is a vector of dummy variables which take value 1 for each period (pre-pandemic, April, May, June, July, September, November 2020, January, March and September 2021), else 0. SC_i is a dummy indicating the level of social capital, measured in pre-pandemic periods and fixed for each individual, while X_i and $X_{i,t}$ are a set of time invariant and time varying control variables in which socio-economic and demographic characteristics of the individuals are included. The interaction term $Covid_t * SC_i$ measures how the relationship between Covid-19 and wellbeing changes with the levels of social capital. The preferred choice of estimation technique would be to use a fixed effects model, which would account for the time invariant unobserved heterogeneity. However, this would also eliminate the effect of social capital which is time invariant. To correct for the impossibility of using a fixed effects estimation, the model includes a set of time-demeaned variables, $\bar{X}_i$, derived as individual-means of the time varying controls across each respondent[3]. This method was proposed by Mundlak (1978) as a way to relax the assumption in the random-effects estimator that the observed variables are uncorrelated with the unobserved variables. Errors are robust and clustered at the individual level. Equation 3.1 is estimated on all of the previously listed proxies for wellbeing and social capital. Importantly, these equations are estimated with the inclusion of all the other social capital variables. This allows to control for any side mechanism through which the different components may jointly affect wellbeing, other than the one attached to each individual variable. Additionally, there is reason to believe that, for example, people who trust more their neighbours will talk to them more frequently and feel more like they belong to their neighbourhood; in essence the social capital components may be correlated.

[3] The interpretation of the estimated coefficients of the Mundlak corrected random effects model are the following: X_{it}, the time varying variables, are estimated as in a Fixed effects model, as the within-person difference over time. X_i, so in this case also social capital, is estimated as a between-individuals effect and lastly, $\bar{X}$ can be interpreted at the difference between the within- and between-individual effects.

A table of the correlation of the social capital components is in the Appendix, see table B.2.

Included controls are age and age squared to account for the non linear relationship between age and wellbeing; gender, employment status (dummies for being unemployed, self-employed or both, using employed as baseline), whether living with spouse, education (dummies for having obtained a BA, Diploma, A levels, GCSE or no education are created), dummies for the area in which the person lives (England excluding London, London, Wales, Scotland, Northern Ireland), ethnicity (dummies for being British White, Irish, other White, Mixed, Black, Bangladeshi-Indian-Pakistani, Chinese-Asian or Arab), household income quintiles, health conditions measured in pre-pandemic periods, household size and individual's risk of contracting a Covid-19 infection according to the NHS. These controls are standard controls of mental health and wellbeing literature.

Social capital is fixed and measured in pre-pandemic periods, as the hypothesis is that individuals' social capital levels affected the relationship between the pandemic crisis and wellbeing. Similarly to a perspective study setting, I analyse the dynamics in wellbeing trends of two groups of people with different characteristics - in this case, social capital - after the advent of an event - the pandemic. This methodology implies that social capital is sufficiently fixed and constant over relatively short periods of times, at least prior to the pandemic crisis. This assumption has been tested by checking earlier UKHLS waves' percentage of people with high social capital and results confirm its stability over time[4]. Admittedly, the pandemic may have changed the form (or the behavioural expression) of social capital from in person to online social interactions. However, the values and attitudes that underlie the proxies of social capital in this paper might have well remained the same; for instance there is no reason to believe that people will not be able to count on their friends or neighbours, or for them to not attend associational activities after the pandemic. The variables used for the construction of the social capital components have not been asked in the UKHLS Covid-19 study (except for one of the four on attitudes towards neighbours). For this reason it was not possible to check the assumption of the stability of social capital after the onset of the pandemic. Given the unavailability of the data, and for the perspective scope of analysis, the interest remains on the pre-measured levels of social capital.

[4]For example, share of people who are active members of Putnam's associational groups is 21% (ci 0.20-0.22) in 2017-2019 and it was 22% three years before (ci 0.220-0.227). Share of people who feel like they belong and frequently talk to their neighbours is 25% (ci 0.24 - 0.26) in wave 9 and it was 29% (0.28 - 0.31) in wave 6 (2014-2016). Share of people who can trust their neighbours and feel they would get help from them was 15% (ci 0.14-0.16) in wave 3 and 18% (ci 0.17-0.19) in wave 6 (2014-2016).

3.4 Results

3.4.1 Descriptive statistics

The average mental distress score over the whole period is 11.56 (on a range of 0-36), and mean life satisfaction is at 5.05 (on a range 1-7). 57% of the sample is female and median age is 57 years old. 50% of the sample is employed, 4% is unemployed and around half of the surveyed population has at least one diagnosed health condition before the pandemic started. In the sample 23% of the interviewed people are active members of Putnam associational groups. 47% of the sample reported to be able to rely on friends or feels that they could open up to them (*personal relations* component). Only around 20% of the interviewed people instead have positive attitudes towards their neighbours, 19% of people trust and can get help from their neighbours and 28% of the interviewed population states they feel like they belong to their neighbourhoods and frequently talks to their neighbours. Table B.1 in the Appendix reports the descriptive statistics of the dependent and control variables.

During the period between April 2020 and September 2021, average subjective wellbeing decreased compared to pre-pandemic periods. Mental distress, proxied by the the GHQ variable, was on average 10.74 (ci 10.62-10.86) in pre-pandemic periods, whereas in April 2020 when the Coronavirus hit, average GHQ increased to 11.95 (ci 11.80-12.11), which is around one fourth of a standard deviation of GHQ in the sample. Figure 3.1 shows the trend of average mental distress over the period. The increase in GHQ scores at the beginning of the pandemic was substantial. Distress decreased sharply during summer 2020 and between November 2020 and January 2021 it reached a peak point with GHQ scores of around 12.17 (ci 12.00 - 12.34).
Life satisfaction instead has changed somewhat less than mental health. Average life satisfaction in pre-pandemic period was 5.31 (ci 5.28 - 5.34) on a 0-7 scale, and hit the lowest point in January 2021 with an average of 4.7 (ci 4.73-4.84), which is around one third of a standard deviation (see figure 3.2).

There are two interesting aspects that emerge from figures on the wellbeing trends. Firstly, the overall trend was negative, although more so for life satisfaction than for mental distress. Indeed GHQ returned almost to the pre-pandemic average by September 2021, whereas life satisfaction did not. Secondly, the pattern of wellbeing fluctuations were consistent between the two measures: wellbeing decreased at the beginning (distress increased and life satisfaction decreased), then rose marginally over the summer (distress decrease and life satisfaction bettered); around the second wave of Covid-19 infections wellbeing plummeted once again and only slightly recovered over the last months of observation.

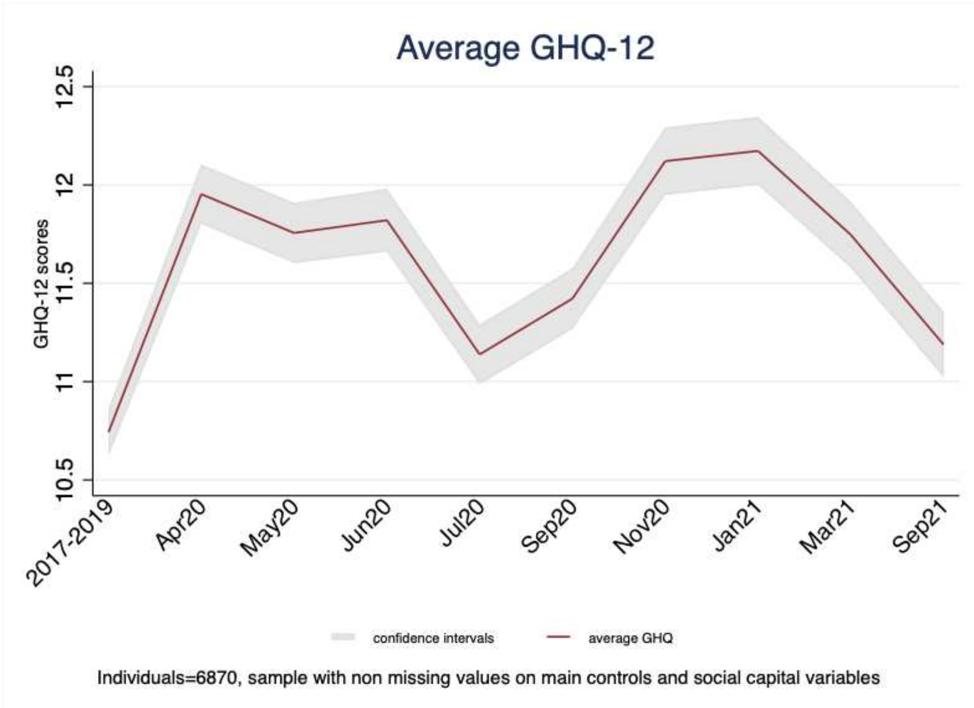

Figure 3.1: Overall mean GHQ-12 score by period of collection with 95% confidence intervals. GHQ ranges from 0-36, 36 being the highest mental distress.

3.4.2 Main results

Table 3.3 reports the results of the estimation of equation 3.1 of the effect of the pandemic crisis and social capital on mental distress, the first dependent variable. The four columns in the table correspond to the estimated results of the wellbeing equation on the four components of social capital described in the previous section.
Results show that compared to the baseline pre-pandemic years, average mental distress increased during the pandemic period. This result is consistent in each specification of the social capital variable, as seen in the first 9 rows of the table, which report the estimated coefficients on the time dummies. Distress was particularly high between November 2020 and January 2021 when UK was hit by the second big wave of Covid-19 infections and the government increased stringency in the lockdown measures.

The point estimate on the social capital proxies is always negative and in almost each case statistically significant, indicating a negative correlation between social capital and distress (coeff: -0.740, 95%ci=$-0.99, -0.4958447$ for *Social Network Support*; coeff: -0.969, 95%ci= $-1.24, -0.70$ for *Personal Relations"*; coeff: -0.202, 95%CI= $-0.48, 0.07$ for *Civic*

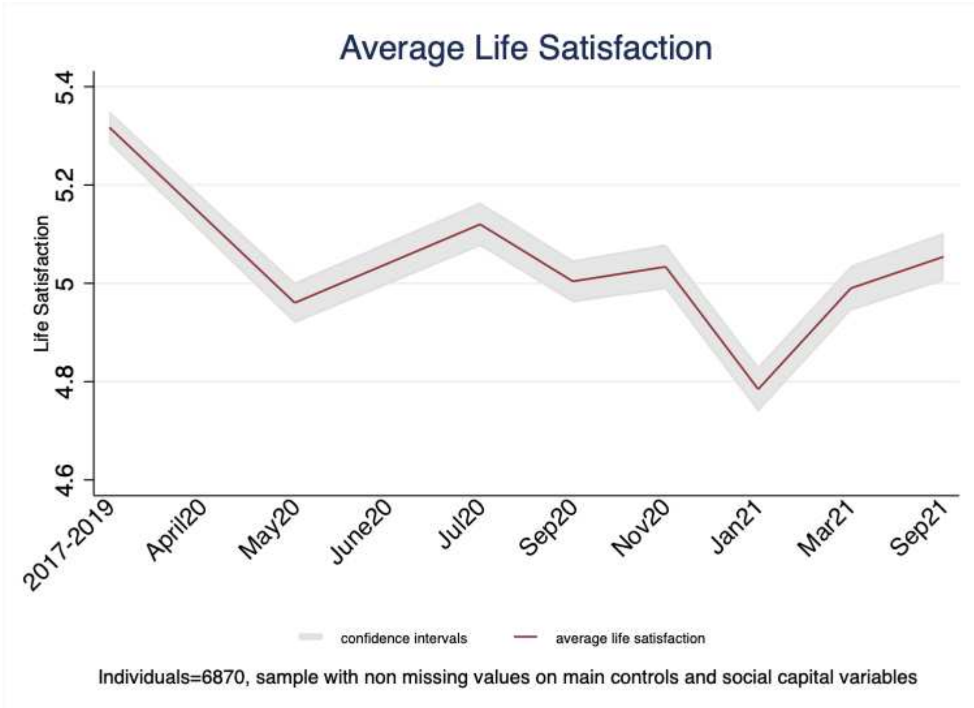

Figure 3.2: Overall mean Life satisfaction score by period of collection with 95% confidence intervals. Life satisfaction ranges 0-7, 7 being the most satisfied possible.

Participation"; coeff: -0.274, 95%ci= $-0.58, 0.0319436$ for *Trust and Cooperative Norms*). This is particularly true for three of the components, *social networks support*, *personal relations*, and *trust and cooperative norms.* For reference on the size effects, the coefficient of having a diagnosed health condition increases mental distress with a coefficient of around 0.91, in each of the specifications.

The coefficients of interest are those on the interaction between social capital and the time dummies. These report how the pandemic affected mental health over time for people with high social capital, compared to people with low social capital. As previously discussed, one of the ways in which social capital positively affects wellbeing may operate via in person activities and social interactions. If this is the case, not being able to attend social activities will have impacted those who care for them the most to a greater extent than those who don't. Results confirm this hypothesis in that high social capital people experienced a greater increase in distress with respect to their pre-pandemic GHQ levels (i.e. they suffered from lower subjective wellbeing during the pandemic period). Positive and significant interaction terms between the social capital proxies and the time dummies indicate a higher suffering with respect to pre-pandemic period for the high social cap-

ital people. As an example, the coefficient on the interaction term between April 2020 and having *Social network support* = 1 (column 1 of the table) is 0.542, significant at the highest level. This suggests that high social capital people's mental distress increased by 0.542 compared to their pre-pandemic level on mental distress. *Social network support* and *Personal relations* are the components that mostly exacerbated the effects of the pandemic for mental health, over the whole period. By adding the coefficients on the time dummies to those of the interactions ($b_1 + b_3$) one concludes that high social capital individuals had a worse mental health deterioration by suffering larger increases in their GHQ scores with respect to pre-pandemic period levels. To continue the example above on the *Social network support* component (column 1), in April 2020 average distress increased by 1.184 and this effect was exacerbated for high social capital people, for whom mental distress increased by $1.184 + 0.542 = 1.726$. A similar effect is found for those who are active participants of Putnam groups, but the increase in mental distress is only significant in June, September and November 2020. People who are high on *Trust and Cooperative norms* seem to have suffered a larger mental health deterioration only in April and September 2020, and to some extent in January 2021. These results are consistent with the more stringent restriction periods that the UK government imposed to contain the spread of the virus, when people had lower freedom of engaging in in-person activities.
These results confirm the first hypothesis for which social capital exacerbated the effects of the pandemic for wellbeing. They suggest that participation and engagement are particularly strong mechanisms for the *Social network support* and *Personal Relations* components in affecting mental health, and that the lack of participation and interpersonal social interactions, i.e. being isolated from others, has a detrimental effect to their wellbeing.

To grasp the overall effect of social capital for wellbeing, however, one ought to look at the coefficients of the social capital dummies summed to those of the per-period interactions: $b_2 + b_3$. The interaction coefficients are in absolute terms lower than the main social capital effect, indicating that social capital is correlated with a lower distress (higher wellbeing) even during the pandemic period. As an example, the *Social network support* coefficient is -0.740 and the interaction coefficient with the April 2020 is 0.542. This implies that the overall effect of social capital in April was $-0.740 + 0.542 = -0.198$, which is indeed still negative. Noticeably, this exercise is depicted in figure 3.3 which shows a visual representation of the marginal effects of social capital for mental health. Average marginal effects (AMEs, defined as the average wellbeing differences between the two groups of people, high minus low social capital) are negative, evidencing a lower mental health (higher distress) of high social capital people than of low social capital people. Results suggest that having high social capital is still beneficial for mental health even throughout the pandemic. If social interpersonal interactions weighted so much on the transmission mechanism from social capital to wellbeing, one could have expected the restrictions to social gatherings to have an overall negative effect of social capital. However this was not the case. This answers to the second hypothesis on the operating mechanism of social capital, that of a social support system that creates wellbeing resilience and allows to fare better even in times of crisis. The components that mostly show significant negative average marginal effects are *social network support* and *personal relations.* Referring back to the theoretical explanation of how social capital works for wellbeing, these results suggest that the social support factor of social capital has an intrinsic value that allowed for wellbeing resilience and to fare better, even when social distancing rules made it difficult to interact with others. Having friends to rely on and whom you can open up to in times of crisis created a base for emotional support and understanding that was particularly good for maintaining a good mental health. Interestingly, for the *social network support* component, AMEs went back to pre-pandemic levels after one whole year of Covid, in September 2021, indicating full resilience only after a very long period. As for *Personal relations*, AMEs have been declining (approaching zero) over time, suggesting that over the long period there is only so much value that social capital can leave to people, if not associated with social interactions as well.

Being an active member in Putnam type associations, which strongly relies on attendance to these groups, has less of a value attached to it if people are not able to interact with fellow members of these associations. Average marginal effects are largely insignificant, indicating no particular benefit for high social capital people throughout the period, or better put, there was no statistically significant difference in the mental health trends of people who are members or not of these groups. Trusting neighbours and being able to get help from them instead showed no positive effect for mental health during the pandemic period, perhaps an indication that this component mostly works via in person interactions, or alternatively, that trust is low (indeed from the descriptive statistics, it appears that only a small percentage of the interviewed population believes people in their neighbourhood can be trusted).

Table B.3 in the Appendix reports the complete table of estimates which includes the control variables. Consistently with the literature, results report that being a woman increases mental distress, whereas being married or in a co-living relationship improves mental health. People living in London have a significantly higher distress levels than those living in other areas of England, however there is no statistically significant evidence of wellbeing effects of enjoying a higher income or employment status.

Table 3.3: GHQ regressions on social capital

	(1) Friends		(2) Personal Relations		(3) Putnam Groups		(4) Trust and Cooperative	
April20	1.184***	(0.106)	1.281***	(0.0919)	1.390***	(0.0908)	1.342***	(0.0878)
May20	1.167***	(0.103)	1.179***	(0.0891)	1.246***	(0.0880)	1.265***	(0.0852)
June20	1.265***	(0.103)	1.271***	(0.0916)	1.314***	(0.0890)	1.375***	(0.0872)
July20	0.758***	(0.101)	0.693***	(0.0900)	0.796***	(0.0876)	0.785***	(0.0855)
September20	0.968***	(0.104)	0.913***	(0.0905)	1.014***	(0.0899)	1.017***	(0.0858)
November20	1.645***	(0.109)	1.640***	(0.0956)	1.712***	(0.0954)	1.829***	(0.0918)
January21	1.813***	(0.121)	1.782***	(0.109)	1.937***	(0.110)	1.900***	(0.105)
March21	1.396***	(0.111)	1.361***	(0.0961)	1.470***	(0.0957)	1.486***	(0.0926)
Sep21	1.011***	(0.111)	0.936***	(0.0982)	0.979***	(0.0954)	1.032***	(0.0927)
SC=1	-0.741***	(0.125)	-0.968***	(0.136)	-0.201	(0.142)	-0.274*	(0.156)
April20 × SC=1	0.542***	(0.151)	0.542***	(0.170)	0.191	(0.176)	0.482**	(0.194)
May20 × SC=1	0.325**	(0.146)	0.486***	(0.162)	0.310*	(0.168)	0.279	(0.184)
June20 × SC=1	0.341**	(0.149)	0.528***	(0.163)	0.472***	(0.174)	0.253	(0.185)
July20 × SC=1	0.155	(0.145)	0.481***	(0.159)	0.146	(0.168)	0.240	(0.181)
September20 × SC=1	0.296**	(0.148)	0.671***	(0.165)	0.398**	(0.170)	0.459**	(0.195)
November20 × SC=1	0.432***	(0.155)	0.712***	(0.172)	0.573***	(0.173)	0.0990	(0.195)
January21 × SC=1	0.337**	(0.156)	0.683***	(0.175)	0.130	(0.176)	0.371*	(0.203)
March21 × SC=1	0.285*	(0.157)	0.584***	(0.175)	0.256	(0.178)	0.224	(0.197)
Sep21 × SC=1	0.0707	(0.154)	0.377**	(0.168)	0.281	(0.178)	0.0692	(0.193)
Constant	14.51***	(0.766)	14.36***	(0.764)	14.36***	(0.764)	14.40***	(0.764)
Controls	Yes		Yes		Yes		Yes	
Number of observations	47169		47169		47169		47169	
Number of individuals	6747		6747		6747		6747	
R^2 within	0.0229		0.0231		0.0228		0.0226	
R^2 overall	0.0872		0.0873		0.0871		0.0871	
R^2 between	0.117		0.118		0.117		0.118	

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Errors are clustered at the individual level. Baseline for time dummies: pre-pandemic period, measured for each individual at one point between 2017 and 2019. Baseline for social capital is 0, i.e. having low social capital.

Included controls: age, age squared, gender, marital status, income quintiles dummies (2-5), macro region dummies, household composition, Both employed and self-employed, self-employed or unemployed (base: employed), bachelor, diploma, A levels, no education (base: GSCE), has previously diagnosed health conditions, is at risk of getting Covid-19 according to NHS and the remaining three social capital component and ethnicity dummies.

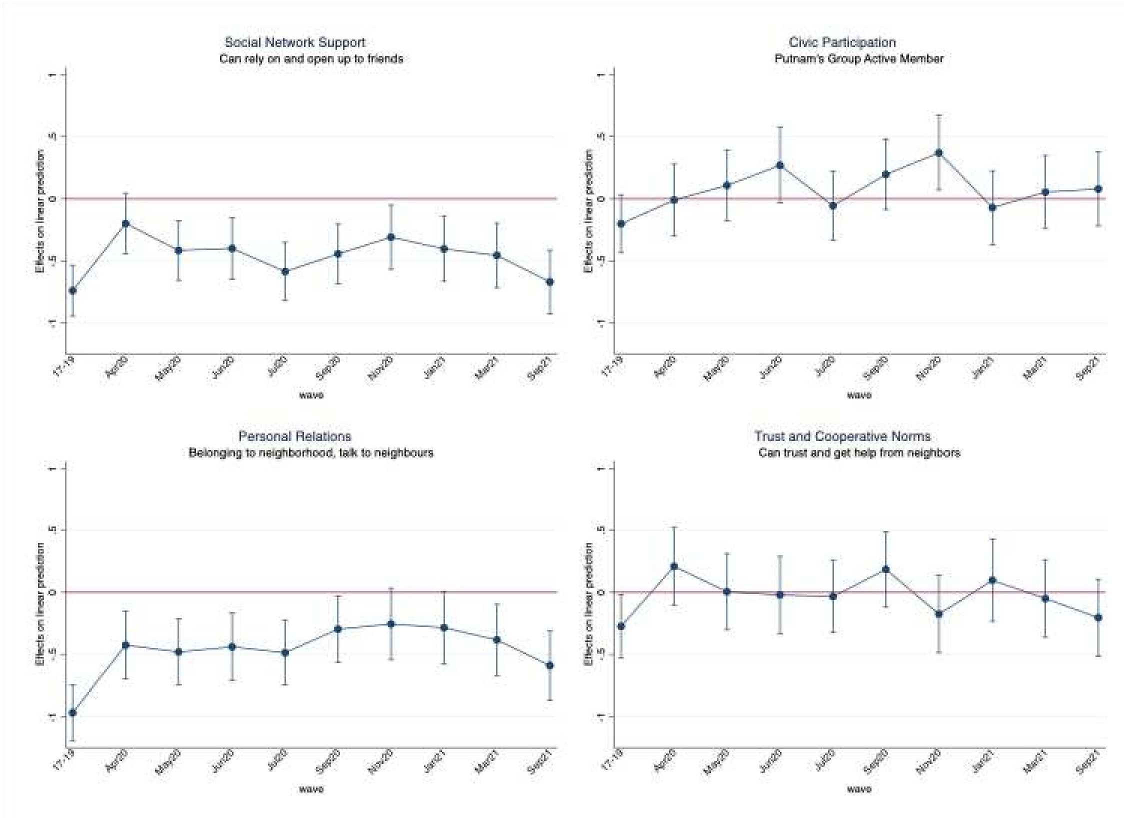

Figure 3.3: Average marginal effects of social capital proxies with 90% confidence intervals. AMEs are derived from the Mundlak estimation results of Table 3.3 on GHQ.

Life satisfaction trends behaved in a qualitatively similar way. Table 3.4 reports the results from equation 3.1 estimated on the life satisfaction variable. Average life satisfaction decreased throughout the pandemic, though to a lesser extent than the increase in distress levels. Social capital in all of its forms correlates with a higher life satisfaction in pre-pandemic years, hence confirming the standard results of the wellbeing literature for which high social capital benefits life satisfaction. The point estimates on the social capital proxies are positive and statistically significant, indicating that at the baseline social capital benefits wellbeing by increasing life satisfaction scores (coeff: 0.226, 95%ci= $0.16, 0.29$ for *Social Network Support*; coeff: 0.340, 95%ci= $0.267, 0.42$ for *Personal Relations*; coeff: 0.166, 95%ci= $0.09, 0.24$ for *Civic Participation*; coeff: 0.0861, 95%ci=$0.003, 0.17$ for *Trust and Cooperative Norms*).

High social capital people also a suffered a larger decrease in their life satisfaction during the pandemic compared to their pre-pandemic satisfaction levels. The b_3 coefficients of the interaction terms of social capital with the time dummies are significant and negative in almost each period of the pandemic for the *Social network support*, *Personal Relations* and *Civic Participation* components of social capital (please refer to columns 1 to 3 of the table). This suggests that the negative effect of the pandemic for life satisfaction has been stronger for high social capital people. Similarly to example for the mental health results, adding the estimated coefficients $b_1 + b_3$ yields, for the *Social network support* component, a reduction in life satisfaction of $-0.339 - 0.137 = -0.476$, i.e. -0.137 lower than the average reduction in life satisfaction in April 2020. All the other components of social capital show a similar result, except for the *trust and cooperative norms* component, for which the negative effect was stronger only in September 2020 and January 2021. These results suggest that people who care for their interpersonal social interactions more have suffered social isolation periods to a greater extent, making in person social activities a strong pathway through which social capital positively affects wellbeing.

To grasp the overall effect that social capital had for life satisfaction throughout the pandemic one needs to look once again at the the social capital main effect in addition to the interaction effects $(b_2 + b_3)$. A visual representation of these average marginal effects is depicted in figure 3.4: the relational components of social capital, *social network support* and *personal relations* variables (top and bottom left panels of the figure), show consistent and significant positive marginal effects of social capital on life satisfaction. Intuitively this is the difference in average life satisfaction per period of the high social capital group minus the average per period satisfaction of those with no social capital. Given the positive sign on the marginals effects, the results shows that high social capital people have been better-off as a group in terms of wellbeing throughout the whole pandemic period. The emotional support, relatedness and values that are associated with social capital allowed for better coping and better life satisfaction for the group of people who are highly endowed with it. It should also be noted, however, that while the *social network support*'s average marginal effects have returned to the original pre-pandemic value by the last observation period in September 2021, the positive effect of *personal relations* has been decreasing throughout the period and did not show signs of reverting to its original level. Being an active participant in Putnam groups has a positive marginal effect on wellbeing at the baseline pre-pandemic period and in some months of the Covid-19 year, when restrictions were laxer. With respect to almost null AMEs in the mental distress results, it would seem that associational groups are good for life satisfaction but don't make any significant difference for mental health. Once again, *trust and cooperative norms* don't make a difference for life satisfaction trajectories.

Noticeably, these results also hold when mental health is controlled for in the life satisfaction regressions. As health and mental health have been found to be determinants of life satisfaction, I include a robustness test to control for this. Results are presented in table B.5 and figure B.1 in the appendix. The social capital main effect is still positive and significant, and so are its interactions with the time dummies, indicating a decrease in life satisfaction for high social capital people, independent of their mental health. Average marginal effects are still significant, suggesting that the values that remain within people with high social capital are independent of mental health.

Table 3.4: Life Satisfaction regressions on social capital

	(1) Friends		(2) Personal Relations		(3) Putnam Groups		(4) Trust and Cooperative	
May20	-0.339***	(0.0323)	-0.359***	(0.0272)	-0.369***	(0.0273)	-0.385***	(0.0261)
July20	-0.248***	(0.0343)	-0.197***	(0.0294)	-0.243***	(0.0291)	-0.250***	(0.0282)
September20	-0.312***	(0.0336)	-0.298***	(0.0292)	-0.342***	(0.0289)	-0.345***	(0.0276)
November20	-0.279***	(0.0343)	-0.313***	(0.0298)	-0.320***	(0.0298)	-0.353***	(0.0285)
January21	-0.483***	(0.0378)	-0.522***	(0.0329)	-0.555***	(0.0332)	-0.557***	(0.0325)
March21	-0.357***	(0.0357)	-0.348***	(0.0305)	-0.394***	(0.0307)	-0.395***	(0.0293)
Sep21	-0.323***	(0.0372)	-0.271***	(0.0316)	-0.328***	(0.0314)	-0.335***	(0.0301)
SC=1	0.226***	(0.0338)	0.340***	(0.0374)	0.166***	(0.0379)	0.0861**	(0.0424)
May20 × SC=1	-0.137***	(0.0456)	-0.151***	(0.0524)	-0.145***	(0.0532)	-0.0915	(0.0596)
July20 × SC=1	-0.0209	(0.0485)	-0.211***	(0.0545)	-0.0597	(0.0563)	-0.0417	(0.0603)
September20 × SC=1	-0.137***	(0.0474)	-0.271***	(0.0529)	-0.147***	(0.0548)	-0.156**	(0.0614)
November20 × SC=1	-0.157***	(0.0493)	-0.135**	(0.0557)	-0.137**	(0.0561)	-0.000881	(0.0635)
January21 × SC=1	-0.206***	(0.0491)	-0.202***	(0.0561)	-0.105*	(0.0569)	-0.115*	(0.0616)
March21 × SC=1	-0.117**	(0.0502)	-0.223***	(0.0568)	-0.0762	(0.0567)	-0.0885	(0.0632)
Sep21 × SC=1	-0.0488	(0.0519)	-0.263***	(0.0588)	-0.0777	(0.0600)	-0.0585	(0.0664)
Constant	5.005***	(0.174)	5.036***	(0.174)	5.042***	(0.174)	5.044***	(0.174)
Controls	Yes		Yes		Yes		Yes	
Number of observations	36671		36671		36671		36671	
Number of individuals	6557		6557		6557		6557	
R^2 within	0.0205		0.0207		0.0199		0.0199	
R^2 overall	0.0609		0.0611		0.0606		0.0606	
R^2 between	0.106		0.107		0.107		0.106	

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Errors are clustered at the individual level. Baseline for time dummies: pre-pandemic period, measured for each individual at one point between 2017 and 2019. Baseline for social capital is 0, i.e. having low social capital.
Included controls: age, age squared, gender, marital status, income quintiles dummies (2-5), macro region dummies, household composition, Both employed and self-employed, self-employed or unemployed (base: employed), bachelor, diploma, A levels, no education (base: GSCE), has previously diagnosed health conditions, is at risk of getting Covid-19 according to NHS and the remaining three social capital component and ethnicity dummies.

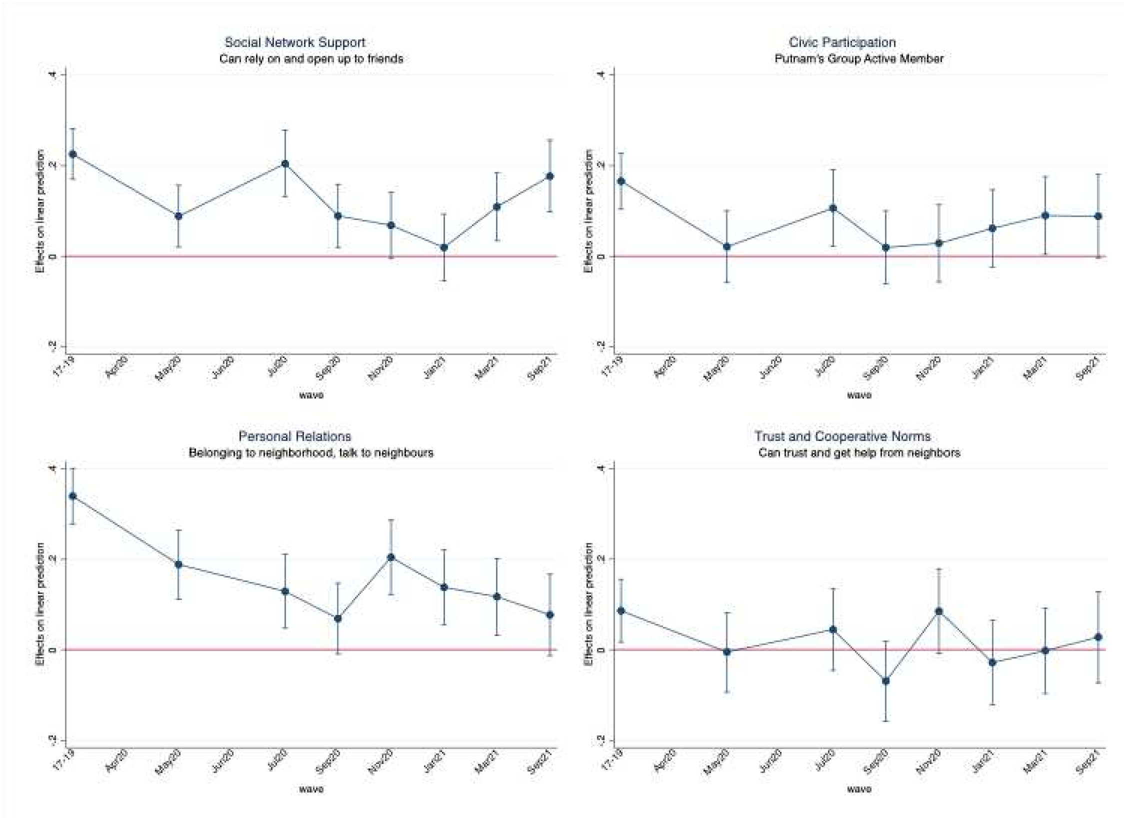

Figure 3.4: Average marginal effects of social capital proxies with 90% confidence intervals. AMEs are derived from the Mundlak estimation results of Table 3.4 on life satisfaction.

To sum up, the results show that having high social capital, especially in the *Social network support* and *Personal relations* components, protects wellbeing even when one cannot enjoy in person social interactions. This suggests that there is more to social capital than just interpersonal relations, in that it gives people values, norms and feelings that stay with them and they can use even when in times of crisis. Indeed, despite having suffered a larger deterioration in their subjective wellbeing levels, this downturn was not high enough as to overturn the positive effects that social capital usually has for wellbeing.

3.4.3 Robustness checks

The Mundlak corrected random effects model does not allow to account for unobserved, time invariant characteristics that might affect the relationship between the pandemic and wellbeing. For this reason I additionally report the results of the estimated equations using a fixed effects model. This robustness test however, it should be noted, does not directly respond to the research questions that are posed in this paper, as the procedure deletes the estimation of social capital all together. The test serves the sole purpose of checking whether the time effects are properly estimated, as also the interaction coefficients, which are retained in the estimation procedure, are a mechanic consequence of an interaction between a time varying variable and a time invariant one. Results of the fixed effects estimations are reported in table B.7 in the appendix. The eight columns are dived in two main sections, four estimations on on mental health (GHQ, columns 1 to 4) and four on life satisfaction (columns 5 to 8). Regressions are estimated on each social capital component and by construction, the main baseline effect is removed by the fixed effects model, hence average marginal of social capital for wellbeing are not calculated. Interaction effects confirm a higher suffering for high social capital individuals in almost each period of the pandemic, for the *Social networks support* and *Personal relations* components of social capital. *Civic participation* and *Trust and cooperative norms* did not exacerbate the negative effects of the pandemic for wellbeing, except for a few months. Life evaluation of individuals with high values on these components of social capital did not significantly change with respect to their pre-pandemic life satisfaction. Overall, fixed effects estimations confirm the pattern of results on the Mundlak corrected random effects model presented in the main analysis.

There are reasons to believe that social capital may be endogenous to mental health and life satisfaction as the association between the two variables may be driven by omitted variables (for instance personality traits) or reverse causality. One example is previous-period wellbeing which shapes individuals' propensity to interact with others and to participate in social activities, their social capital. In the analysis presented above, most of the social capital variables are taken from the same survey years as the first observation period of wellbeing, making it endogenous to wellbeing at least in that period. To overcome this issue, one possibility is to include lagged wellbeing among the controls. Exploiting the longitudinal nature of the UKHLS data, I perform an additional test for which I include lagged GHQ. For instance, if the social capital proxy was collected in wave 9 (2017-2019), the lagged GHQ for each individual is the GHQ score that was collected in wave 8. Results from this robustness check suggest that the inclusion of past GHQ only marginally reduces the social capital effects for wellbeing. As seen in table B.6, the correlation between social capital's main effect and GHQ decreases in magnitude and the interaction effects loose some of the significance, suggesting that high social capital people only suffered greater decreases in their wellbeing in a few of the months. As for the average marginal effect of enjoying higher social capital, the effects still hold albeit uniquely for the initial period of the pandemic and for the *Social network support* and *Personal Relations* components, as seen in the left panels of figure B.2. Once Covid infections increased once again and lockdown measures became more stringent around November 2020 and January 2021, there is no indication of a resilience mechanism at play for social capital on mental health. The implication of this test is that some of the social capital effect on mental distress are attributable to past wellbeing levels.

Another way of correcting for endogeneity issues between social capital and wellbeing is to perform a Hausman Taylor estimation. The random effects estimator is not consistent when social capital is correlated with unobserved individual fixed effects, and the latter procedure would eliminate the estimation of the time invariant social capital variable all together. The Hausman Taylor estimation procedure is designed to overcome this issue of an endogenous time invariant variable by instrumenting it with the exogenous time varying regressors X_{it} (Hausman and Taylor, 1981). Results of this estimation procedure[5] are reported in the table B.8 in the appendix. Once again results are confirmed: the decrease in wellbeing during the pandemic year was higher for the high social capital people. This result is particularly true for the *Social network support* and *Personal relations* components, whereas the *Trust and cooperative* and *Civic participation* components significantly reduced individuals' wellbeing in the first months of the pandemic and in September and November 2020. The average marginal effects cannot be computed with the Stata user written command, but by adding the social capital main effect estimated coefficients to the interaction coefficients, one may see that they would be below zero for the relational components and almost 0 for the remaining two components, in the case of the mental distress. Similar patterns are true for life satisfaction, however, as in the main analysis, the *Civic participation* component seems to create some resilience for life satisfaction. Hence overall the Hausman Taylor estimation confirms the results of the Mundlak corrected random effect model, while correcting for endogeneity and for the inconsistency in the estimated coefficients of the main analysis. This was not used as main model merely because of the lack of possibility of correctly estimating the confidence intervals, hence the significance of the average marginal effects.

3.5 Discussion

The pandemic has caused the UK to adopt measures to contain the spread of Covid-19 contagions that mainly included social distancing and limitations to mobility. Extensive research on the wellbeing consequences of the pandemic has found that some subgroups of the population have been particularly negatively affected, such as those belonging to an ethnic minority, the unemployed and females. However, these are some of the most common negative correlates of subjective wellbeing and the pandemic exacerbated this negative relation. The aim of the analysis I carry out in the present paper is to asses if social capital created a difference in how people suffered the effects of the pandemic. Similarly to a perspective study, the analysis focuses on the wellbeing differentials for the high and low social capital groups of people after the onset of the pandemic. Results show that firstly, compared to pre-pandemic periods, people with high social capital experienced a higher

[5] The Hausman Taylor estimation was performed on Stata using the xthtaylor command, specifying in the endogenous list variables the social capital variables, that are fixed and time invariant.

mental distress and lower life satisfaction. The hypothesis is that mandated isolation and social distancing affected people who care for their social interactions more than others, and that a factor contributing to the positive effect of social capital for wellbeing is interpersonal, real life interactions with others. Once these are taken away from people they will suffer and those who are usually more socially engaged will suffer exacerbated effects. Secondly, results show that people with high social capital suffered less than people with low social capital. This confirms the hypothesis that social capital creates values and support system that are available to people in times of crisis and allows them to cope better. Both results vary depending on the considered component of social capital. Indeed, social capital components that have to do with the personal sphere of relations, such as *Personal relationships* and *Social network support*, are the ones that exacerbated the effects of the pandemic to a greater extent, while also allowing for better wellbeing levels compared to the low social capital group of people.

There are some limitations to the study. Firstly, the issue of endogeneity between social capital and wellbeing is difficult to address, though results are robust to a various robustness checks. Secondly, the analysis is performed on a panel setting in which the time dimension is not measured on a constant interval of time (but the results - omitted for brevity - hold even when I narrow the sample available for the analysis to include only periods with equal time intervals). Thirdly, I am unable to disentangle the effects of lockdowns from the overall *crisis* effect of the pandemic. Indeed I referred interchangeably to "the pandemic" and "Covid-19 crisis" in a way that accounts for everything that the period under analysis entailed: anxiety, containment policies, fear and lockdown effects are not directly discernible and hence I do not make any claim that it was the containment policies or the lockdown periods that *caused* the average decrease in wellbeing. Additionally, adopting a more rigorous approach to modelling social capital will help to better understand its effects for wellbeing. In the present analysis I relied on measures that were readily available in the data, but these are not a comprehensive list of social capital proxies that one may use. Some components, such as civicness and trust in institutions are missing. Researchers and institutions should consider the benefits of investigating social capital more in depth and consistently in time. Formalising the concept of social capital, as well as its components and structures, and providing established operational definitions (measures that have been validated, compared to benchmarks and frequently measured) will allow for more convincing analyses of its effects for wellbeing, as well as for other outcomes. To this regard, what is missing from my analysis and in general from the literature are structural equation models, mediation analysis or convincing identification strategies to claim a causal relation between the social capital and wellbeing. With the present analysis I provide brief insights on the mechanisms via which social capital increases wellbeing, but further research into these effects would benefit from a more formal approach, and unrelated to the health crisis, which are beyond the scope of this paper.

Lastly, this paper does not account for any social capital change after the onset of the pandemic. This was largely due to unavailability of data, but future research will need to assess if and how social capital changed as a consequence of such particular times. The measures that have been implemented to contain the spread of contagions relied on limiting social interactions. The intuitive consequence is that social capital, or last the expression of it, diminished. However, this ought to be formally assessed. Indeed multiple things may have happened. On the one side, the frequency of social interactions decreased, but it is unclear if this is limited to the two Covid-19 years, 2020 and 2021, or if people have been so scarred that on average, the trend will continue diminishing (as an example, please refer to Borkowska and Laurence (2021), who find that social cohesion diminished in June 2020, especially in poorer and most deprived areas). On the other hand, it may be that instead feelings of reciprocity and togetherness increased as a way to stick together in times of crisis. This would entail an uptake of volunteering rates, charity donations and increased levels in trust. Some, scarce, evidence of Britons volunteering for the NHS showed that this was the case, but future research will have to assess this trend in the future. This is of particular importance as worrying research findings show that social capital has been on a declining trend in the past few decades (Putnam et al., 2000; Bartolini et al., 2013; Bartolini and Sarracino, 2015).

Nevertheless, the added value of this study is that the exploration of the effects of social capital on mental health and life satisfaction may help to address some important clinical and epidemiological questions such as ensuring collective challenges of national safety without coming at too high costs for individuals' wellbeing. Social capital is in fact a resource that helps communities provide public goods by facilitating collaborative actions to bolster public health (House et al., 1988; Pretty, 2003; Snyder-Mackler et al., 2020; Bartolini et al., 2020), but also it is a resource that may be used by each individual to increase their resilience to adversities. Studying the transmission mechanisms from social capital to wellbeing allows to understand how long the "wellbeing-limit" for social capital deprivation is before there are too large negative consequences for wellbeing. The Covid-19 crisis behaved as a natural experiment of an exogenously induced reduction in social interactions, at least in the mandated isolation periods. The evidence I report may help policy making in understanding the wellbeing consequences of sustained periods of isolation, low social engagement and to address issues such as loneliness. These results could also advise on how to invest in social capital policies that will ultimately allow people to have more socially active lives and have better emotional support, higher trust and feelings of belonging and relatedness. Indeed the values that stem from having social networks and having devoted time to maintaining them remain within people, allowing for wellbeing resilience even when they cannot enjoy the in-person social interactions.

3.6 Conclusion

Employing a representative sample of the adult population of the UK, I investigate how different levels of pre-existing social capital affected the relationship between the Covid-19 crisis and subjective wellbeing, measured as mental distress and life satisfaction, and I posit the transmission mechanisms from social capital to wellbeing. Results show that, firstly, higher social capital individuals exhibited larger decreases in wellbeing compared to their pre-pandemic levels. Secondly, results show that on average high social capital people enjoy better mental health and higher life satisfaction than low social capital people, even when in times of a health crisis. Both result were mainly driven by the *Social network support* and *Personal relations* components of social capital, which created larger wellbeing differences between high and low social capital people, and created a larger drop in wellbeing compared to pre-pandemic levels. Average marginal effects computed on the difference in wellbeing between high and low social capital groups suggest that the pandemic did not eliminate the positive wellbeing effects of having high social capital. Negative marginal effects on the mental health measure throughout the whole period indicate that the average mental distress score (GHQ) is always lower for high social capital individuals, making them *on average* better off even during the pandemic period. Similarly, positive average marginal effects on the life satisfaction measure suggest that people with stronger social engagement enjoyed higher wellbeing on average throughout the period. Results also show, however, that long periods of distress and isolation decrease average marginal effects, suggesting that keeping people away form their social relations for too long will eventually reduce the resilience effect that social capital may have for wellbeing. This is evidence that there is a residual effect of social capital that goes beyond face to face interpersonal interactions, which are values, relatedness and emotional support that allow to fare better in times of crisis and guarantee wellbeing resilience.

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Chapter 4

Loneliness increases the probability of worse mental distress development during Covid-19

Abstract[1]

This paper uses a non-parametric model to analyse the mental distress development in the UK during the Covid-19 pandemic. Using data from a recently published article by Ellwardt and Präg (2021), I use latent class analysis to explore the possibility that the development of mental health, measured as distress with the General Health Questionnaire, may have been heterogeneous across the population. I subsequently use a multinomial logistic model on the latent trajectories of distress to analyse how individuals' characteristics relate to each trajectory *ex-post*, and I analyse the extent to which loneliness shapes the probability of individuals of being either trajectory. I report the results in terms of average marginal effects, which reflect the average change in the probability of being on either trajectory for a change in each of my predictors of interest. My findings suggest that the probability of being on a trajectory of continuously high distress was 26.67% higher for people who are often lonely, and 13% higher for those who are sometimes lonely, compared to non-lonely people. I conclude with a discussion of the costs of loneliness for the society and the economy.

Keywords: *Subjective wellbeing, General Health Questionnaire, loneliness, trajectory analysis, latent class models, Group based trajectory modelling*

[1] This chapter has been extensively discussed with a PhD colleague of mine, Nita Handastya, who will likely write future versions of this paper with me.

4.1 Introduction

The global lockdown policies that were introduced to control the spread of Covid-19 affected the world drastically. It is by now well documented that the effects reached the personal spheres of health and wellbeing of people all over the world, with results showing significant increases in distress levels and decreasing psychological wellbeing and mental health (Banks and Xu, 2020; Fujiwara et al., 2020; Daly and Robinson, 2022).

One's capability to respond and cope with crisis periods is determined by many factors. Typically, pandemic-induced mental health stressors have been studied using a priori expectations of their effects on average wellbeing in the population. This approach requires an ex-ante hypothesis of such stressors and focuses on how these affected mental health. However, it does not allow to detangle heterogeneities in the way people fared. I argue that the development of mental health may have been heterogeneous and hiding different patterns. In the present paper, I aim at analysing the possibility of mental health heterogeneities by exploring the trends of illbeing (mental distress) among the UK population. I therefore carry out an inductive analysis of mental health, to then reveal the patterning of individuals' characteristics associated with mental health development differences, without assuming *a priori* that certain characteristics were more likely to affect mental health. In particular, I allow for the possibility of multiple trajectories of distress throughout the period by classifying individuals based on their mental health development over time and not on prior expectations. To do this, I use a latent class model. This method analyses the information on individuals' mental health and finds patterns of mental health development across individuals that are deemed to be mutually exclusive and independent of individuals' characteristics. This approach takes a step back from assuming that mental health is a linear function of different elements and rather answers the question of "was the development of mental health similar for everyone in the population?". Subsequently I employ a multinomial logistic model on the latent trajectories of distress to analyse how individuals' characteristics relate to each trajectory ex-post, and I report how loneliness shapes the probability of individuals of being either trajectory. The advantage of using latent class analysis is to allow for a deeper insight into the development of mental distress trajectories that would otherwise remain unexplored in standard exploratory analysis.

I base my approach on earlier similar works by Pierce et al. (2021) and Ellwardt and Präg (2021) who modelled mental health trajectories using latent class analysis on United Kingdom data until September 2020 and March 2021, respectively. Both attempted to identify the predictors of belongingness to a particular trajectory by focusing on socio-economic indicators. I exploit one additional time period, analysing these trajectories until September 2021, and argue that although socio-economic status and the standard stressors of illbeing are good predictors of the assignment to either latent class of mental health development (Ellwardt and Präg, 2021; Pierce et al., 2021), other factors should be considered. I am particularly interested in studying individuals' loneliness and I posit that it is a strong predictor of worsening distress. In a prospective study setting in which I inspect the development of mental distress after the onset of the Covid-19 crisis, I predict how people fared based on their loneliness levels before the pandemic started.

The proposal to explore loneliness is based on the literature outlining its relationship with mental health. The Covid-19 pandemic saw a significant migration to digital telecommunication as a form of social interaction. However, digital telecommunication does not entirely replace the need to meet in person, as human interactions are more beneficial for one's mental wellbeing (Teo et al., 2019). Intuitively, the absence of social interaction is linked to a worsening of one's wellbeing. Loneliness has been associated with higher levels of depression and a reduction in life satisfaction (Borg et al., 2006; Golden et al., 2009). This phenomenon has been found across different cultures (Cacioppo et al., 2006; Losada et al., 2012), indicating that it is a universal experience. A longer-term longitudinal study by Cacioppo et al. (2010) further confirmed the relationship between loneliness and depression even after controlling for demographic variables and factors such as stressful life events, social support, and neuroticism. The authors further stated the importance of greater attention to loneliness as a key to maximise the likelihood of individuals remaining healthy and functional across their life span (Cacioppo et al., 2010, pp 460). This indicates a relationship between loneliness and the broader concept of health. For instance, in Northern Ireland loneliness increased the likelihood of mental distress (measured with the General Health Questionnaire) by more than five times (Shevlin et al., 2013). Further studies have been conducted to explore its general consequences and mechanism (Hawkley and Cacioppo, 2010). Research on mortality (Holt-Lunstad et al., 2015) and mental health problems (Wang et al., 2018) further complemented the effect it imposes on the wider landscape, such as public health (Leigh-Hunt et al., 2017) and its economic cost (Mihalopoulos et al., 2020). I discuss the consequences of loneliness and illbeing in detail later on in the paper.

This study contributes to the literature on loneliness and mental health during the Covid-19 pandemic. Previous studies have used various methodologies in different countries. I exploit trajectory analysis as it allows the opportunity to observe the heterogeneities that might have arisen throughout the population, that are not necessarily determined by the individual characteristics that research would assume. In France, a study using a similar methodology was done by Lu et al. (2022). They focus on anxiety and depression measures (GAD-7 and PHQ-9 respectively) rather than on self-reported mental health status. They identified who was the most vulnerable in terms of worsening mental health, including having had Covid-19 as a predictor. For the UK, one of the earliest papers that employs similar methods to the one proposed in this paper is that by Pierce et al. (2021), who used mixed model latent class analysis to identify mental health trajectories in the UK. A follow-up study was performed by Ellwardt and Präg (2021) who focused on the analysis of demographic characteristics of individuals and how prevalent psychological distress was. Both studies used a General Health Questionnaire (GHQ) measure of mental distress, either in its continuous scale (0-36) or as a dichotomous scale of presence of absence of severe illbeing, such as I did. I use the data from Ellwardt and Präg (2021) and confirm their results that mental distress followed four different patterns, ranging form people who did not suffer any distress throughout the period, to part of the population who instead suffered considerable increases in their illbeing. The descriptive analysis of the composition of each class of mental distress development also confirms the usual findings for which women, young people and single people where over represented in the high distress class. My contribution pertains the analysis of loneliness, in that people who are sometimes or often lonely were most likely to be in the high suffering group, and those who are never lonely were mostly in the no distress class. Additionally, I was able to exploit an extra period of analysis that suggests a strong recovery in the largest part of the population, which was not shown in previous studies.

4.2 Data and methodology

The data used to carry out the analysis is from Ellwardt and Präg (2021), who employ the Understanding Society UK Household Longitudinal Survey (UKHLS). This is a comprehensive longitudinal survey of members of a representative sample of households in the United Kingdom. In 2020, during the Covid-19 pandemic, Understanding Society collected online and phone interviews in the months of April, May, June, July, September, and November 2020 as well as in January, May and September 2021. During this period, participants from the main Understanding Society sample were asked to complete short web-surveys (with a telephone option in some months). This survey covered a wide range of topics including the impact of the pandemic on the welfare, wellbeing and labour outcomes of UK individuals. These surveys included a core content which was repeated in each period and rotating questions as well. Individual data from the main survey and the Covid-19 study can be linked with the eligible sample to complete the special release being adults who completed the last two waves of the main survey, between 2016 and 2019 [2].

The information collected in the surveys includes individual-level mental health conditions before (from the main UKHLS survey) and during the pandemic period (from the UKHLS Covid-19 survey). The analytic sample includes individuals who completed at least three interviews about their mental health conditions at any point in the observation period (N=8996). This is necessary to detect a trajectory in their mental health states. Unlike Ellwardt and Präg (2021) who use information until March 2021, my period of observation is a time series that spans from April 2020 to September 2021, with an additional observation of pre-pandemic information collected in wave 9 of the UKHLS main survey,

[2] Additional information on the Covid-19 sample selection can be found in the user guide.

between 2018 and 2019.

The main variable of interest is mental distress, measured with the General Health Questionnaire (GHQ). This is a subjective wellbeing measure that aims at detecting current psychiatric disturbances (Goldberg and Blackwell, 1970). The GHQ is a reliable and consistent measure to detect distress throughout the general population (Pevalin, 2000). To collect information on psychological distress, participants are asked twelve questions such as "Have you recently been feeling unhappy or depressed?", and can respond with four possible answers: 1 "Much more than usual"; 2 "Rather more than usual"; 3 "No more than usual"; 4 "Not at all". The detailed list of questions and answers is reported in the Appendix, table C.1. People who answer 1 or 2 are assigned value 1 and those who answer 3 or 4 are assigned a value 0. The summation of the 12 questions makes the GHQ-12 score (0-12) but I opt for the caseness dicotomization of the measure such as to detect a presence or absence of psychological distress. The cut-off point has been discussed in the psychiatric literature to be 4 out of 12 for presence of distress (Goldberg, 1988). Hence, in each period, the individual will be assigned 1 or 0 on their GHQ score depending on whether they reach the cutoff. Meanwhile, loneliness is assessed with the direct question 'how often do you feel lonely?'. Responses are recorded using three levels: hardly ever/never, some of the time, often, which I use as a categorical variable.

4.2.1 Formalisation of the method: group-based trajectory model

To detect the prevalence and distribution of mental health disturbances throughout the pandemic period I follow the same approach as in Ellwardt and Präg (2021) and use a group-based trajectory model (GBTM). Latent class mixture modelling, a specific type of group based trajectory model, allows to identify clusters of individual trajectories of changes in a variable without having any prior expectation of its distribution (Collins and Lanza, 2009; Jones and Nagin, 2013). This data reduction technique probabilistically distributes individuals within a population in different latent classes which are mutually exclusive between groups. It allows to find groupings of individuals who share similar data patterns to determine the extent to which these patterns may relate to variables of interest. In my case, each class represents a subpopulation of individuals who had a similar trajectory of mental health throughout the ten observed periods. The estimated parameters in group-based trajectory modelling are the product of a maximum likelihood estimation, which have the advantage of being consistent and asymptotically normally distributed. Two key outputs of GBTM are the shape of the trajectory, typically defined by a polynomial function of time, and the probability of trajectory group membership. The group-based approach for modelling trajectories is intended to provide a flexible method for identifying distinctive clusters of individual trajectories within the population and for profiling the characteristics of individuals within the clusters (Jones and Nagin, 2013).

Formally, let $Y_i = y_{i1}, y_{i2}, ..., y_{it}$ denote the vector of longitudinal sequence of measurements of individual i's mental distress over T periods, where $T = 10$. Let $P(Y_i)$ be the probability of Y_i. The objective of group-based trajectory modelling is to estimate a set of parameters β that maximise the probability of Y_i, $P(Y_i)$. β defines the shape of the trajectories and the probability of class memberships. The shape of the trajectories is described by a polynomial function of time, which I specify as third order polynomial. The model assumes that individual differences in trajectories can be summarised in a finite set of different polynomial functions of time and each set corresponds to a trajectory class k. Additionally, let $P(Y_i|k)$ be the probability of Y_i given the membership in class k, and let π^k be the probability of a randomly chosen individual of belonging to class k (essentially, a memberships probability). π^k is unknown and has to be estimated.

The likelihood function requires the aggregation of the K conditional likelihood functions $P(Y_i|k)$ to form the probability of the data Y_i. In other words $P(Y_i)$ is the sum across the k classes of the probability of Y_i given i's membership in classes k weighted by the probability of membership in class k. The equation reads as follows:

$$P(Y_i) = \sum_{k=1}^{K} \pi^k P(Y_i|k; \beta^k) \tag{4.1}$$

where

$$P(Y_i|k; \beta^k) = \prod_{t=1}^{T} p(y_{it}|k; \beta^k). \tag{4.2}$$

Here, $p(.)$ is the distribution of y_{it} conditional on membership in class k. I specify the distributional form of $p(.)$ to be a binary logistic distribution, as mental distress is measured as a dummy of presence or absence of distress, hence $y_{it} = [0, 1]$. For any class k, conditional independence is assumed for the sequential realisations of the elements in Y_i, y_{it}, over T.

Finally, since one of the purposes of latent class analysis is to assign individuals to latent classes, I point out that the probability of each individual of belonging to either latent class K, given his response vector Y_i is obtained by a Bayes rule. The most common classification rule is modal assignment, which amounts to assigning each individual to the latent class with the highest posterior probability (Magidson and Vermunt, 2004)

$$(\pi^k|Y_i) = \frac{\pi^k \times P(Y_i|k; \beta^k)}{P(Y_i)} \tag{4.3}$$

4.2.2 Implementation of the model and class specification

I construct latent class mixed models to identify the distinct trajectories in mental health using the *traj*[3] command in Stata 17, in which I specify the distribution of the data on mental health $p(.)$ to be logistic (as mental health is measure as presence or not of distress (0,1) in each period). The optimal number of trajectories (i.e. latent classes) k is determined by comparing goodness of fit statistics of models with a varying number of trajectories, starting with $k = 1$, and sequentially increasing k by one. To assess the goodness of fit of the model with each different specification of k classes I compare three measures: BIC (Bayes Information Criterion), AIC (Akaike Information Criterion), and LL (Log Likelihood). In table 4.1 I report the fit statistics of each model with different k trajectories from 1 to 6. The choice of the model that best represents the data should be given by the one with the lowest fit statistic. Additionally to the fit statistics I however base my decision for the best model to use on the posterior probabilities of class membership (the higher, the better), entropy (a measure of information) and visual interpretability of the trajectories figures. Similarly to Ellwardt and Präg (2021), I find that the optimal fit is $k = 4$. Beyond this point, the fit improves only partially (the reduction in the AIC and LL was smaller), posterior probability rates decrease as well as the entropy measure, and the number of individuals assigned to each class becomes relatively small. Additionally, some of the trajectories are rather similar and do not exhibit discernible heterogeneity.

Table 4.1: Fit Statistics

	BIC	AIC	LL	% TRAJ1	% TRAJ2	% TRAJ3	% TRAJ4	% TRAJ5	% TRAJ6
traj 1	-33038.61	-33024.4	-33020.4	100					
traj 2	-26898.13	-26876.82	-26870.82	68,8	31,1				
traj 3	-26431.65	-26392.58	-26381.58	54,0	30,2	15,8			
traj 4	-26263.1	-26206.26	-26190.26	51,1	7,5	25,2	16,3		
traj 5	-26221.83	-26147.23	-26126.23	27,7	29,1	23	4,8	15,3	
traj 6	-26189.6	-26097.24	-26071.24	35,4	13,8	22,8	17,2	5,5	5,2

Note: Goodness of fit statistics and class prevalence for k latent trajectories model. N=8996.
BIC: Bayes Information Criterion, AIC: Akaike Information Criterion, LL: Log Likelihood.

In a second step I use a multinomial logistic regression to examine the individual characteristics that are associated with each class. The dependent variable in this model is a categorical variable of the highest posterior probability of being assigned to each latent class. Higher means of the estimated posterior probability indicate a higher chance of individuals of being assigned to the correct trajectory class. These posterior probabilities in my case are 0.84 for the first trajectory, 0.62 for the second, 0.73 for the third and 0.84 for the fourth, suggesting a good sorting of individuals in the trajectories. I discretely assign each individual to the best latent trajectory for which they exhibit the highest probability,

[3]Documentation can be found in Jones and Nagin (2013).

and examine whether pre-pandemic levels of loneliness and socio-economic variables are associated with being on either trajectory. In my results I report the average marginal effects (AMEs) of an average change in the trajectory's probability when each of the studied covariates increases by one unit. My main independent variable is loneliness, as my main focus is to examine the role of pre-pandemic loneliness levels on how people fared throughout the period. Additional covariates that I include are similar to those of Ellwardt and Präg (2021), namely controls for region of residence (dummies for the countries of Scotland, Wales, Northern Ireland with England as baseline), age categories (<24, 25-44, 45-64 and >65), gender (a dummy for female=1 and male = 0), race (White = 0 or Non-White = 1), and whether living with a partner (dummy = 1). I control for earnings (log monthly and mean imputed) and if the person has lost a sizeable amount of their income in post pandemic period. Additionally, I include controls for having children at home, being a single parent, and whether the person reported diagnosed health conditions and had Covid-19 symptoms. Lastly, I include controls for socio-economic status. Similarly to Ellwardt and Präg (2021), I followed the official classification by the National Statistics Socio Economic Classification (NS-SEC) (Office for National Statistics, 2016). There are several ways to narrow down the group, but the most common is to draw 3 categories: working class, intermediate workers, and professional workers[4]. Interestingly, a fourth category that indicates a own-account working status[5] is typically attributed to the intermediate worker category. However due to their precarious own-account working nature, I included an additional dummy to note this category separately. Since labour market status has been previously found to impact mental health, I expect that those in the category of own account working might exhibit a significant worsening of their mental health in a period of economic downturn as their financial security might have come under risk.

4.3 Results

Results from the latent class mixture modelling suggest that psychological distress followed four distinct trajectories throughout the pandemic. A visual representation of such trajectories can be found in figure 4.1. Similarly to Ellwardt and Präg (2021), I find that 51.1% of participants' likelihood of distress was continuously low (trajectory 1, continuously good mental health) whereas 8% of people started off in 2019 with very low levels of distress, but once the pandemic hit their distress levels dramatically increased to then return to pre-pandemic levels after summer 2020 (trajectory 2, recovering mental distress). $25,2\%$ of the population exhibited an elevated distress majorly in the second part of the pandemic, though with some increases in the month of April 2020 (trajectory 3, deteriorating

[4]See Krieger (2003).

[5]Employer of a small establishment (agriculture; non-agriculture), and own account worker (agriculture; non-professional).

mental health). Lastly, 15,3% of the population started out in 2019 with higher mental distress, and this worsened throughout the Covid period as well (trajectory 4, continuously poor mental health). In April and for the whole period of the first Covid-19 wave their distress was extremely high and only started to lower again September 2021, however still not returning to pre-pandemic levels. Ellwardt and Präg (2021) found that the population was distributed in the four trajectories with 53.2% of people in the first trajectory of now distress, 8.0% of people in the second, 24% in the third trajectory and 14.8% in the high mental distress trajectory. These results are consistent with a few other studies who found similar patterns both in the UK (Pierce et al., 2021) and in France (Lu et al., 2022) using similar methods for modelling latent class analysis. In particular, my results replicate those of Ellwardt and Präg (2021) but I additionally include to the time series of the observational period September 2021. By then, two groups, trajectories 3 and 4 (deteriorating mental health and continuously poor mental health) started to show a decrease in mental distress levels, indicating a trend towards recovery. This result is positive in that it indicates that by the end of the period around 31% of the population started to suffer from lower mental distress.

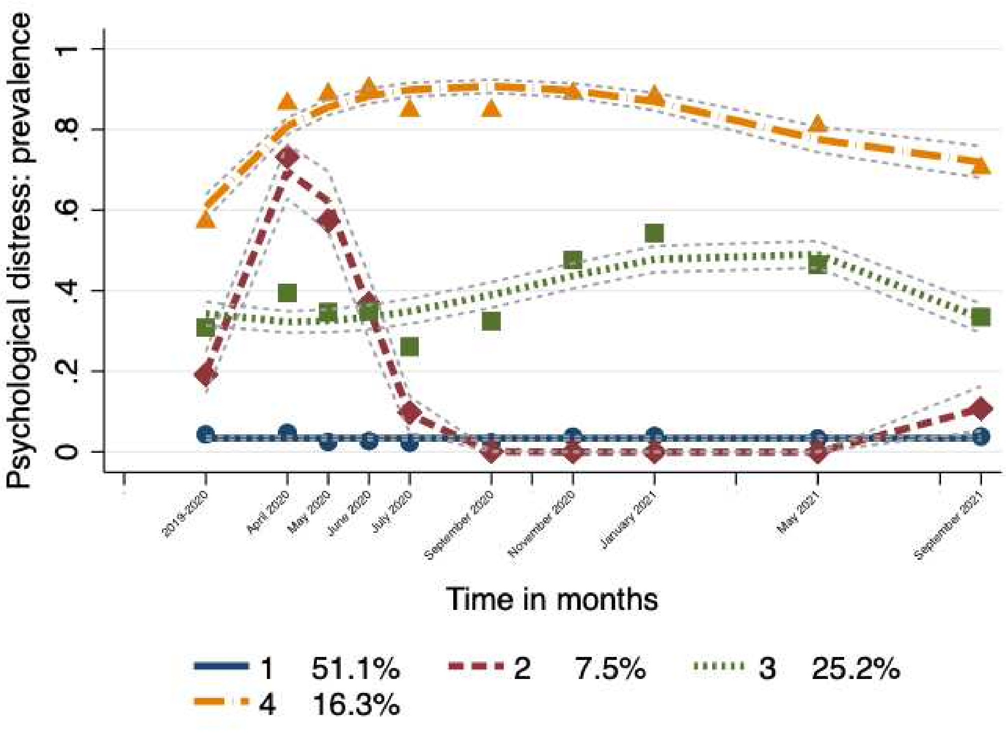

Figure 4.1: Trajectories of mental health throughout Covid-19 period.

The distribution of individual characteristics across latent classes of mental distress is shown in Table 4.2. This reports the ex-post classification of people in to each latent class according to their mental health trajectory. People with consistently good mental health (low distress) were more likely to be older than 45 years old, living with a partner, white and never lonely. In contrast, those experiencing elevated distress (trajectory 4) were young, female, non-white, single parents and belonging to the working-class category of socio-economic status. People who recovered after a first elevated distress period (trajectory 2) instead were those who have children at home, had Covid-19 symptoms, and do not have any medical condition. People who are sometimes or often lonely were highly represented in the group who had consistently poor mental health and so were people in the working class category.

I run a multinomial regression model to examine the factors that are associated with the four distinct trajectories. The assigned trajectories of each individual served as dependent variable in the multinomial regression. For ease of interpretation, I report results as average marginal effects (see figure 4.3a) which reflect the average change in the probability of being on either trajectory for a change in each of my predictors of interest. My findings suggest that the probability of being on trajectory 4 of continuously high distress was 26.67% higher for people who are often lonely, and 13% higher for those who are sometimes lonely. This suggests that from an initial probability of 16.3% of being in this class, for often lonely people this increased to 42.97%. Similarly, the probability of being on trajectory 2 of recovering mental health was 2.9 percentage points higher for often lonely people and 1.4 percentage points higher for sometimes lonely individuals. Instead, for people who are sometimes or often lonely, the initial probability of being on a continuously low mental distress trajectory was respectively 46 and 22 percentage points lower than the initial 51.1% of trajectory 1 (continuously good mental health). This translates to saying that people who are lonely have a 4.9% probability of being in a good mental health state, compared to any other not lonely person.

My results also confirm previous findings that age and gender were good predictors of how people fared. In particular, they suggest that being older than 24 years old increased the probability of being on the continuously good mental health trajectory, whereas younger people were more prone to higher distress and females had around 10 percentage points lower probability of sustained good mental health (continuously low distress). Having children at home was associated with around 4 percentage points higher chance of being on trajectory 3 of deteriorating mental distress. As for socio-economic class, own-account workers had a probability of being on the continuously high mental distress trajectory which was 3.1 percentage points higher than the initial 16.3% probability, and the working class instead showed a 6.2 percentage points higher probability of being on the continuous low mental distress trajectory. Instead, no significant differences in changes in probabilities were detectable in the intermediate class of workers. I report the classification of job descriptions into each socio-economic group in the Appendix C.1.

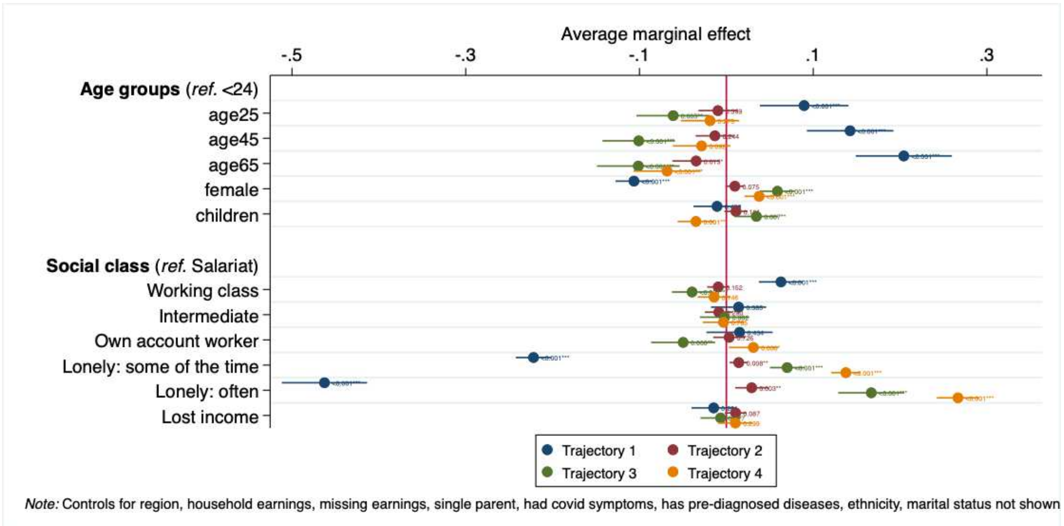

Figure 4.2: Coefficient plot of Average Marginal Effects of multinomial regressions of belonging to either trajectory.

(a) Notes: Average change in a trajectory's probability when a covariate increases by one unit, from a multinomial model in which the outcome variables are the trajectories of psychological distress: (1) continuously low, (2) temporarily elevated, (3) repeatedly elevated, (4) continuously elevated. Error bars represent 95% confidence intervals. Reference category for loneliness is "never lonely". AMEs of the controls for region, household earnings, missing earnings, single parent, had Covid symptoms, has pre-diagnosed diseases, ethnicity, marital status are not shown. Own elaboration of Understanding society data.

4.4 Discussion and concluding remarks

Findings from the mental health and wellbeing literature during Covid-19 generally agree on the overall decrease in subjective wellbeing and increase in mental health issues. In this study, I suggest that reporting overall or subgroup averages masks different experiences that people may have encountered during the pandemic. Using a latent class mixture model I identified four distinct trajectories of how people fared with their lives during this crisis period. My findings suggest that around half of the population did not show worrying trends of mental health deterioration, while 40% of the interviewed population fared much worse, with continuous or repeatedly high levels of distress. In particular, a quarter of the population started off with relatively low mental distress levels before the pandemic and exhibited an increasing trend of mental distress which spiked in September 2020. However, differently from what shown in other studies that only analysed until that

Table 4.2: Proportion of covariates by trajectory

	BEST CLASS 1 Mean	BEST CLASS 2 Mean	BEST CLASS 3 Mean	BEST CLASS 4 Mean	Chi-2 test p-value Mean
Age24	0.04	0.08	0.09	0.09	0
Age45	0.45	0.44	0.39	0.43	
Age65	0.23	0.11	0.16	0.14	
Female	0.51	0.64	0.67	0.69	0
Non-white	0.13	0.14	0.13	0.16	0.025
Partner	0.78	0.71	0.69	0.63	0
Children	0.37	0.48	0.45	0.39	0
Single parent	0.04	0.08	0.09	0.11	0
Covid symptoms	0.25	0.34	0.33	0.37	0
Is healthy	0.55	0.59	0.51	0.42	0
SES: Working class	0.29	0.27	0.28	0.31	0.007
SES: Intermediate	0.13	0.13	0.16	0.15	
SES: Salariat	0.47	0.49	0.49	0.44	
SES: Own Account worker	0.10	0.09	0.07	0.09	
Lonely: Hardly ever or never	0.75	0.53	0.50	0.30	0
Lonely: Some of the time	0.23	0.39	0.39	0.48	
Lonely: Often	0.02	0.08	0.10	0.210	
Log household income	7.44	7.49	7.35	7.28	0
Lost income	0.35	0.44	0.37	0.36	0.01
N	4127	401	1726	1164	

period (such as Pierce et al. (2021)), I find that in March and September 2021 their distress levels started to lower, indicating that a year after the beginning of the pandemic things started to improve and people recovered. Instead, the remaining part of the population had a significant worsening in their mental health at the onset of the pandemic in April 2020, but quite quickly reverted back to a better mental health state. These results suggest that the mental illnesses that resulted from the pandemic crisis may have been, at least for part of the population, a temporary drop in wellbeing. Future research in the coming years will have to confirm this or understand if instead mental health will not have returned back to pre-pandemic levels. My results further suggest that the distribution of mental distress was not equal across the population. Other than the risk factors that have been commonly associated to poorer mental health such as being female, younger and belonging to minorities, I find that people who typically suffer from poor social relations, i.e., who declared that they felt sometimes or often lonely before the pandemic had much higher chances of suffering from very poor mental health before and during the pandemic. In contrast, the chances of detecting lonely individuals in the continuously good mental health group were extremely small.

The increasing epidemic of loneliness calls for policies that aim at facilitating and improving the number and quality of interpersonal relations. Though I acknowledge that loneliness may have to do with the personal sphere of choice of individuals of being social or not, not everyone who is lonely is so by choice, but rather they feel isolated, left out and detached from others and society. Additionally, there are many public health and economic consequences of having a lonely population. Indeed, loneliness is associated with lower wellbeing and higher mental health problems, something I have confirmed also in the present study, which is in itself economically and socially costly. Mental health has been found to cost the economy at least £70 billion through lost output and £10 billion in increased healthcare costs in the UK (Layard, 2017). Workers who are mentally ill are found to be less productive, have more physical problems, and increase state welfare costs and cause reductions in tax revenues (Layard, 2017). Similarly, a study from Australia finds that mental health issues are estimated to cost the economy up to 60 billion dollars annually in health care, lost productivity and many other direct and indirect costs (Holt-Lunstad et al., 2015). Similar figures stem from loneliness research. In the US, a study on Medicare beneficiaries found that individuals who were socially isolated cost the health system 1643 dollars more per year than similar individuals who had good social networks (Shaw et al., 2017). People affected by solitude may shy out of economic activities and have lower trust and bridging social capital which have been identified as important factors for economic growth (Muringani et al., 2021). Lastly, Morrish et al. (2022) found that improving loneliness levels can mitigate the occurrence of being unemployed.

Given the evidence of the negative consequences of loneliness on mental health and the economy, and that the incidence of distress has increased for a large part of the population since the pandemic started, there is the need to tackle these issues. Examples of the effectiveness of interventions that address loneliness are from McDaid et al. (2017), who conducted a systematic review of the cost effectiveness of these interventions and estimated the costs over a ten-year period to be between £1,700 to £6,000 (depending on age and severity of loneliness) with an estimate of return on investment of between £2 and £3 per £1 invested over a five-year period. This estimate was what helped the government to better understand the impacts of loneliness and then resulted in the appointment of UK's Minister for Loneliness.

My results are further evidence that suffering is unequally distributed among people and social scientists should be concerned not only about average trends, but also about the heterogeneity in suffering. Trajectory analysis allows to disentangle this heterogeneity in distress trends and what relates to it the most. These results are quantitative evidence that lonely people have very high chances of being in a continuously high suffering group, higher than other individual characteristics that may normally worry researchers and policymakers. For instance, the higher distress typically found in the younger population is something that they may grow out of, whereas being lonely and with poor social connections can be a more persistent situation, leaving them in a sustained mental distress situation for a long time. The consequence of this is that even after the more critical period of the pandemic, there are still many people living in constant distress and who need ad-hoc support.

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Chapter 5

Do epidemics impose a trade-off between freedom and health? Evidence from Europe during Covid-19.

This chapter has been co-authored with Stefano Bartolini and Francesco Sarracino.

Abstract

The extent to which governments' policies for the containment of Covid-19 relied on voluntary compliance or on enforced social and economic restrictions, differs substantially across countries. Why so? The answer to this question is important because economic and psychological costs of an epidemic surge with the severity of restrictions. As the risk of infections increased in recent decades, it is critical to understand what enables a society to contain epidemics with mild restrictions of citizens' freedoms. Our answer is that trust in others and in public institutions allows for less stringent containment policies. We collected data on policy stringency, speed of decline of new contagions and mortality during the first wave of Covid-19 in Europe. After accounting for various confounding factors, we find that governments of more trustful countries introduced less stringent policies, burdening the society with lower economic and psychological costs. This did not come at the expense of public health: holding policy stringency constant, high trust countries report lower mortality, as well as lower number and faster decline of new contagions than others. We conclude that the trade-off between freedom and health during epidemics depends on a country's trust level: the more people trust others and institutions, the more this trade-off fades. Therefore, promoting trust in others and in institutions is a critical challenge for contemporary societies.

Keywords: *Covid-19; Social Capital; Interpersonal Trust; Institutional Trust; Policy stringency; Containment policies; Freedom*

5.1 Introduction

There are two main policy options for the containment of an epidemic. The first is centralized control and enforcement, the second relies on citizens' voluntary cooperation (Harari, 2020). During the first wave of Covid-19, governments' decisions differed considerably in the extent to which they leaned towards one of the two options. Little research effort has been devoted to investigate what drives these international differences, whose importance goes beyond Covid-19. As the risk of infections increased in the XX century (Smith et al., 2014), it is critical to understand what enables a society to contain epidemics with limited sacrifices of people's freedoms. By analyzing 27 European Union member states during the first wave of Covid-19 pandemic in 2020, we show that trust in others and in major public institutions allows governments to safeguard people' s freedom and health. This relationship has not been tested before.

The paradigm of centralized control is China. The Chinese government reacted to the Covid-19 epidemic by invading the privacy of its citizens, monitoring their smartphones, using hundreds of millions of cameras for facial recognition and body temperature measurement, forcing people to monitor and report their medical conditions, employing drones to enforce shelter-in-place orders. In this way, Chinese authorities quickly managed to control the epidemic by identifying infected individuals, tracking their movements and contacts, and enforcing rules.

The alternative model, adopted in other East Asian countries such as South Korea, Taiwan, and Japan, relies on people's responsibility and civic behavior. In these countries, swab positives complied with shelter-in-place measures and people cooperated in mass testing, tracing and social distancing, for the most part voluntarily. In just one day, on April 9, 2020, nearly half a million South Koreans were tested for coronavirus, a level of participation that would be impossible to impose on a recalcitrant citizenry.[1] These countries avoided extreme personal mobility restrictions and closure of airports. This strategy has also been a success, with low mortality and economic costs. European countries too implemented a wide range of containment strategies. For instance, during the first wave of the epidemics many Southern European countries introduced stringent lock-down compared to Northern Europe, which, on the contrary, adopted milder policies. Figure D.3 in the Appendix graphically shows the countries' variation in stringency in the policies they adopted to contain Covid-19.

[1] KCDC, Updates on COVID-19 in Republic of Korea 5 April 2020.

No country relied on enforcement or voluntary cooperation exclusively. Governments rather adopted a mix of the two extremes. However, what matters is on which side of the two extremes this mix hangs, because this heavily affects the psychological and economic costs of an epidemic. Such costs increase with the severity and duration of the containment policy. For instance, the economy contracted more in the European countries that introduced more stringent policies (the correlation coefficient between the average stringency in 2020 and the yearly growth rate of GDP is -23%). This is consistent with the estimated global economic cost of the pandemic: between \$8 and \$16tn (Dobson et al., 2020). As for mental health, it is well documented that post-traumatic stress, depression, anxiety, insomnia, confusion, anger and stress soared during lockdown and quarantine (Rajkumar, 2020; Dong and Bouey, 2020; Rossi et al., 2020; Kim and Jung, 2020; Fiorillo et al., 2020). From this point of view, centralized control exerts a heavier toll on society because it relies on long and severe restrictions of economic and social activity.

What makes governments lean towards centralized surveillance or citizen involvement? Frey et al. (2020) document that autocracies imposed more stringent measures than democracies. The influence of the nature of the political system is apparent in East-Asia, where democracies had a different approach from autocratic China. But what about Europe, where governments are all democratically elected? What is the root of the differences that we observe in European containment policies?

We provide evidence that European governments of countries with higher pre-existing trust in others and in public institutions adopted less stringent policies than others. The likely reason is that trust between people and in institutions is critical for solving large-scale collective problems such as epidemics, without resorting to severe limitations of citizens' mobility. In high-trust contexts, the countermeasures can count on small daily behaviors whose effectiveness relies on widespread compliance based on cooperation. A large literature shows that in a society, the level of interpersonal trust is a fundamental indicator of the ability of its members to cooperate (Putnam, 2000; Fukuyama, 1995). Adherence to containment behaviors yields a classical social dilemma (Ostrom, 1991): it is costly for the individual, while the single individuals' contribution to the collective goal is negligible. Trust overcomes exactly such problem by increasing the willingness to cooperate. Experimental evidence suggests that the belief that most others will cooperate encourages conditional cooperators to do the same (Fischbacher et al., 2001; Shinada and Yamagishi, 2007). Governments of countries with low levels of trust in others may have little confidence in the cooperative capacity of their citizens, which would lead them to prefer enforcement to voluntary compliance. As for trust in institutions, it is an important determinant of citizens' compliance with public health policies (Chuang et al., 2015; Rönnerstrand, 2014). In countries where trust in institutions is low, governments could expect low citizens' compliance. This would favor centralized control.

Europe is an ideal case for testing our hypothesis. Political, economic, and socio-cultural differences can affect governments' choice in ways it is difficult to control for. Testing the relationship between trust and policy stringency requires a set of reasonably homogeneous countries, with substantial differences in their levels of trust. Europe offers exactly these features. Moreover, Europe is an ideal candidate to test our hypothesis because Covid-19 was the first example of serious epidemic since 1918. East and Far East countries had already experienced epidemics in recent years. Their memory about what to do and what behaviours to adopt to tackle the crisis was fresh, hence they may have adopted containment behaviors independently from trust in others and in institutions.

Our findings that countries where trust is high adopted less stringent policies is robust to various specifications of our measure of trust. Moreover, it is independent from the average income and income inequality of a country, the preparedness of its healthcare system to face the emergency, the severity of the epidemic outbreak, as well as the frequency of social contacts, and the health conditions of its population. Laxer restrictions of citizens' freedoms in high trust countries did not come at the expense of public health. These countries experienced faster decline of new contagions, and a lower number of new positive cases around the peak. We also did not find a statistically significant association with mortality at the peak. Summarizing, our results suggest that, during the first wave of the pandemic, countries with pre-existing high levels of trust introduced less stringent policies, while protecting the health of their citizens.

The paper is organized as follows. Section 5.2 clarifies the contribution of our paper to the literature. The data and methods used in the analysis are presented in Section 5.3. Section 5.4 illustrates our results, and section 5.5 discusses and summarizes our findings.

5.2 Literature review

More than thirty years after Margaret Thatcher's "there is no such thing as society", another conservative British PM, Boris Johnson, epitomized the profound reassessment of the importance of collective action triggered by Covid-19: "One thing I think the coronavirus crisis has already proved is that there really is such a thing as society". Other European PMs agree. Angela Merkel emphasized that "taking action collectively as a society is key", while Emmanuel Macron claimed: "I am appealing to your sense of responsibility and solidarity." Giuseppe Conte stated: "The responsible behavior of each one of us will be fundamentally important". The Covid-19 narrative acknowledges the role of social capital for successful containment of the pandemic (Bowles and Carlin, 2020), a role which is supported by growing evidence.

Governments' awareness of the importance of social capital for policy outcomes may affect their choice. In high social capital countries, governments may expect widespread voluntary compliance, thus opting for non-stringent measures. Recent literature explores the relationship between trust and policy stringency, however results are still inconclusive. We add to the existing literature in analyzing the relationship between trust and stringency measures and linking this relationship to a possible trade-off between freedom and health, which we find to be fading in higher trusting societies.

Frey et al. (2020) focus on some political factors underlying the ability of a society to contain epidemics with mild restrictions on freedoms. They analyze 111 countries and find that autocratic regimes imposed more stringent lockdowns relative to democratically accountable governments. Moreover, democracies were approximately 20% more effective in reducing geographic mobility, holding constant the policy stringency. In a study of the US, Brodeur et al. (2021) find no evidence of trust in determining either the likelihood of implementation or the timing of stay at home orders, while they do find that counties that are governed by Democtrats were more likely to implement stay at home policies (Brodeur et al., 2021). Similarly, Romano et al. (2021) test the hypothesis that the policy stringency in a given country depends of the levels of cooperation and trust in others of its citizens. Their finding is once again that stringency is unrelated to both measures. However, similarly to out findings, in a study of European countries, Toshkov et al. (2021) find that societies with higher interpersonal trust and trust in the government reacted slower to the spread of the pandemic and with less decisive containment measures. Surprisingly, Chiplunkar and Das (2021) find instead that, on a wider and more international dataset, higher trust in the government increases the likeliness of more stringent policies.

Yan et al. (2020) instead study the strength of social norms within societies and the institutional arrangements (centralized vs decentralized regime scheme) to evaluate the combinations of the measures that determined the policy stringency of a country and they posit the trajectories of policy stringency depend on how they interacted with population response and cultural orientation.

Data on mobility has received considerable attention in the literature on Covid-19, as changes in mobility at the onset of the epidemic are considered a good proxy of compliance to social distancing. Most research emphasizes the role played by pre-existing levels of social capital in reducing mobility right after the Covid-19 outbreak. High political trust has been found to be associated with large reduction in non-essential mobility across European regions (Bargain and Aminjonov, 2020). Another study shows that during the early phase of Covid-19, voluntary social distancing was high for individuals with high sense of civic duty. This holds across U.S. counties and individuals, and European regions (Barrios et al., 2020). Borgonovi and Andrieu (2020) show that mobility reduced faster and more dramatically in US counties with a high index of participation to religious, volunteering and community activities. Mobility dropped more sharply in Italian provinces with high social capital, as measured by an index including blood donations, trust in others, and newspaper readership (Durante et al., 2020). Similarly, Bartscher et al. (2020) find that high electoral turnout predicts faster decline in mobility across Italian areas. Interestingly, Schmeltz (2020) documents that a substantial share of the German population would cooperate more to containment behaviors under voluntary than under enforced implementation. This result suggests that appeals to voluntary participation may encounter less opposition than coercive interventions. Some evidence concerns also the influence of partisan differences on mobility. Pro-Trump counties in the 2016 U.S. presidential election exhibited 14% less physical distancing between March and May 2020 than pro-Clinton counties, resulting in higher COVID-19 infection and fatality growth rates (Gollwitzer et al., 2020). Lastly, Petherick et al. (2021) found that countries who are endowed with higher interpersonal trust have complied to physical distancing more than countries with low levels of trust. However, Ding et al. (2020) find that there is a difference in social distancing outcomes when considering social capital as either community engagement or individual commitment to social institutions: in US when community engagement is stronger, people might be more reluctant to socially isolate. In turn, when individual commitment to broader social institutions is stronger, people are more likely to incur the costs of isolating in order to contribute to public health.

As for the other two outcome variables considered in this study, the dynamics of contagions and mortality, few papers analyze their relationship with social capital and, specifically, with trust. Bartscher et al. (2020) document lower excess mortality in Italian areas with higher electoral turnout and a slower increase in Covid-19 cases in the areas of seven European countries where electoral turnout was high. Additionally, in U.S. counties and states, an increase in social capital correlates with lower Covid-19 infection rate and mobility (Varshney and Socher, 2020). More recent studies find that at US county level during the first wave of contagions (between March and July 2020), Covid-19 spread and deaths fell when increasing social capital from the 25th to the 75th percentile (Makridis and Wu, 2021). Similarly, Carson and co-authors find that social capital encourages Covid-19 prevention, measured as policy stringency. Their finding is that states with higher social capital show a lower number of cases and slower spread of contagion compared to lower social capital states with similar levels of stringency (Carson et al., 2021). Lastly, Lenton et al. (2022) found that in 150 countries, generalised trust (measured as trust in others) positively correlates to a higher resilience to Covid-19, which they measure as the rate of decline in number of cases and deaths from the peak to the zero cases/deaths. They however also find, differently from our results, that trust in politics and in the government, and policy stringency are not correlated with the decline in the number of Covid-19 cases and deaths. They argue that the effect of stringent containment policies on the spread of the pandemic is not straightforward as most governments applied similarly stringent restrictions but had varying success in lowering cases numbers and deaths. Their argument is that this is true partly because more stringent governments tend to be associated with less trusting societies. In this paper, we test this hypothesis and expand on their work by confirming that this hypothesis is correct, as governments of less trusting countries will rely on enforced measures rather than on their citizens' cooperative behaviors.

The evidence from the Covid-19 crisis is consistent with previous findings on the role of social capital in preventing and controlling epidemics such as SARS, Ebola, and Zika outbreaks, as well as the various strains of HN influenzas. Social capital was associated with the intention to receive vaccination, to wash hands more frequently, and to wear a face mask during an influenza pandemic in Taiwan (Chuang et al., 2015). Similarly, in Sweden and the U.S., social capital correlates with the intention to receive the vaccination against the H1N1 pandemic in 2009 (Rönnerstrand, 2014). Low social capital, on the other hand, can explain low compliance with control interventions during the Ebola outbreak (Blair et al., 2017; Vinck et al., 2019). Evidence from China suggests that high social capital areas are more likely to obey to rules, thus reducing their close contacts behaviour during the early stages of COVID-19. Trust, acceptance of social norms and media publicity of social norms all negatively correlate to close contacts behaviour and positively to self-quarantining, indicating that higher social capital areas are more abiding to rules. (Liu and Wen, 2021)

However, not all components of social capital may provide a positive contribution to contain infection outbreaks. The epidemiological literature suggests that the frequency of face-to-face contacts can enhance the spread of infections (Béraud et al., 2015; Fumanelli et al., 2012; Leung et al., 2017; Mossong et al., 2008; Zhang et al., 2019). High levels of intergenerational interaction provided by extended families have been indicated as a possible cause for the severity of the pandemic in East Asia. Normally protective factors for older people' s health, such as family ties, turned into a risk factor in the context of an epidemic with a marked age-related fatality profile (Chen et al., 2020; Jordan et al., 2020; Li et al., 2020; Zhou et al., 2020). Analyzing 63 countries, Di Gialleonardo et al. (2020) find that the number of infections and deaths was higher in countries where family ties are more important. However, this effect may be limited in time. The number of COVID-19 cases was initially higher in high social-capital areas, but it decreased more quickly. This result holds for 7 European countries (Bartscher et al., 2020) and Japan (Fraser and Aldrich, 2020).

5.3 Data and method

Our dataset results from merging various sources. Our period of analysis is the first wave of the Covid-19 pandemic, from the beginning until the end of May 2020. In subsection 5.3 we detail the variables used in the analysis, their source and any transformation that we applied before running the statistical analysis. Subsection 5.3 details our empirical approach.

Data

Outcome variables The main dependent variable (*Government response stringency*) is the government's policy stringency measured at the time of the peak in new contagions[2]. We use the Government Response Stringency Index available at Our World in Data[3]. Time-series on response stringency are available for many countries since the beginning of 2020. Stringency is measured on a 0 to 100 scale, where 100 represents the strictest measures. The Oxford COVID-19 Government Response Tracker[4] collects indicators about policies concerning school closures, workplace closures, public events, restrictions on gatherings, public transport, public information campaigns, stay at home measures, internal movements restrictions, international travel controls, testing policy and contact tracing. The stringency index is a composite measure which adds the nine ordinally scaled indicators, and it is rescaled to vary from 0 to 100.

Less stringent policies introduced by countries with high levels of trust may come at the cost of reduced effectiveness in the epidemic control. To account for this possibility, we use three alternative dependent variables: *new deaths at the time of the peak (per one million)*, *new positive cases at the time of the peak (per one million)*, and the *rate of decrease of new contagions*. The source for Covid-19 data is the Coronavirus Resource Center of the John Hopkins University[5]. The rate of decrease of new contagions is computed and made available by the Hume Foundation[6].

Trust Trust in others and in institutions are two key components of social capital, sometimes indicated as horizontal and vertical social capital, respectively (Scrivens and Smith, 2013). Social capital is the set of social norms, values, and understandings that allow a society to cooperate to achieve common goals (Putnam, 2000). Our main independent variable is *Index of confidence*, an index measuring the extent to which people trust others and institutions. Six measures of confidence in institutions and trust in others inform the index. Figures are extracted from the last wave of the European Quality of Life Survey (EQLS)[7].

[2] When we refer to a variable measured at the time of the peak, we mean the average value of the variable measured over a period of seven days centered on the peak.

[3] `https://ourworldindata.org/grapher/covid-stringency-index?tab=table`.

[4] Please, refer to Hale et al. (2020) for more details.

[5] `https://coronavirus.jhu.edu/map.html`.

[6] `https://www.fondazionehume.it/societa/litalia-e-gli-altri-bollettino-hume-sul-covid-19-4`.

[7] EQLS surveys are conducted in pan-European countries every four years by randomly selecting a sample of adult population per country and are administered face-to-face. Data have been collected since 2003 in four waves (2003, 2007, 2012, 2016), however for the purposes of this paper, we utilize information from the most recent wave. Information about the EQLS and the data are available at `https://www.eurofound.`

The wording of the question on interpersonal trust is "would you say most people can be trusted or that you can't be too careful in dealing with people?". Answers range on a scale from one ("you can't be too careful") to ten ("most people can be trusted"). The wording of the questions about confidence in institutions is "Please tell me how much you personally trust each of the following institutions. Please tell me on a scale of one to ten, where one means that you do not trust at all, and ten means that you trust completely". The list of institutions includes: government, parliament, local authorities, police, the press and judicial system.

The index of confidence in others and institutions is computed after applying a Principal Component Analysis (PCA) to the trust and confidence variables included in the last wave of the European Quality of Life Survey (for more details about the PCA, see D.3. Figure D.1 shows the ranking of the confidence index in each of the analysed countries.). These variables are originally encoded on a scale from one to ten at individual level. We dichotomized each variable by assigning value one to respondents who chose a score of seven or higher, and zero otherwise. Assigning a threshold of seven allows us to compute the share of people reporting high trust in others and in institutions. Subsequently, we computed the national shares using sampling weights. Cronbach's alpha of the confidence index is 0.95.

To check the sensitivity of our results to the choice of variables included in the index, we allow for the following alternative specifications of the index of confidence:

- $confidence_1$: the PCA is applied only to trust in others, in the government and in parliament;
- $confidence_2$: the PCA is applied only to trust in the government and in parliament;
- $trustinothers$: we use only the share of people trusting others.

Controls To account for factors that can confound the relationship between the index of confidence and our dependent variables, we include the following set of control variables: the *logarithm of GDP per capita (constant 2010 US$)* and the *Gini index*. GDP proxies for the amount of economic and healthcare resources that a country can mobilize. Greater resources allow countries to do better testing, contact tracing and rules enforcement, thus affecting the outcome of containment policies. The Gini index of income accounts for the fact that high income inequality seems to create population groups that are particularly vulnerable to Covid-19. An example is the disproportionate risk of mortality among low-income groups and ethnic minorities in the U.S. and U.K., two highly unequal countries

europa.eu/surveys/european-quality-of-life-surveys/european-quality-of-life-survey-2016.

(Aldridge et al., 2020; Kirby, 2020; Finch and Hernández Finch, 2020). These data are extracted from the World Development Indicators (WDI)[8]. Most governments motivated restrictions with the need to avoid the collapse of the healthcare system, in particular of intensive care units. To account for this, we control for the *number of beds in intensive care units (per 100.000 people)* (Rhodes et al., 2012). We also control for the *average number of deaths during the week preceding the lockdown (per one million)* to account for the different degree of emergency that countries faced. The stringency of governmental restrictions may increase with the size of the most vulnerable population groups, as the profile of Covid-19 mortality is disproportionately related to age and chronic diseases. Moreover, elderly people with chronic diseases have higher risk of contagion because they often live grouped in nursing homes, which proved to be fertile terrain for the spread of Covid-19. Therefore, we included a control for the expected number of life years affected by a chronic disease. This variable is computed by subtracting the average number of healthy life years[9] from the average life expectancy by country (sourced from World Development Indicators).

We include a control for the share of people who meet others less often than once a month (*share of people that rarely meet others*). As the frequency of face-to-face contacts is supposed to enhance the spread of infections, Covid-19 may affect more the countries where people meet others more frequently than elsewhere. This control variable is computed by country using data from the last wave of the EQLS (2016). The original variable ranges on a scale from one (meeting others face-to-face nearly every day) to five (never meet others). We assigned value one to respondents who declared to meet others less often than three times a month, and zero otherwise. We then computed the country-level shares of people who rarely meet others by applying sampling weights.

Schmeltz (2020) shows that those who were brought up under the coercive regime of East Germany would support enforced measures more than those who grew up in democratic West Germany. This suggests that the experience of state coercion may be a source of cross-country differences in the way people respond to policies in Europe. This in turn, could affect governments' policy choice. All Eastern Europe until 1989 and Spain, Portugal and Greece until the late 1970s, were governed by dictatorships for many decades. Therefore, we include among our controls a dichotomous variable identifying young democracies. In a different specification this variable includes only former socialist governments, excluding Spain, Portugal and Greece that were ruled by far right dictatorships.

[8]https://databank.worldbank.org/source/world-development-indicators.

[9]Data are sourced from Eurostat. The exact measure is healthy life years in absolute value at birth, for individuals who do not have disabilities, and data for each included country is available at https://ec.europa.eu/eurostat/statistics-explained/index.php/Healthy_life_years_statistics.

Methods

The models we estimate use a sample of 27 member states of European Union for the governments' response stringency, for the number of new deaths and positive cases due to Covid-19, whereas the sample size decreases to 19 in the case of the speed of decline of new contagions. Table D.2 in the Appendix details the list of countries available for each variable. Table D.1 in the Appendix details the list of variables used in present study.

To test the hypothesis that countries with more trust in others and in institutions adopted less stringent policies, we use Ordinary Least Squares with robust standard errors. Indeed, the results of the Breusch-Pagan test (Breusch and Pagan, 1979) for homoskedasticity indicate to reject the null hypothesis in all our specifications. Formally, we estimate the following equation:

$$GovtResponse_c = \alpha + \beta_1 \cdot Confidence_c + \beta_2 \cdot X_c + \varepsilon_c \tag{5.1}$$

where the subscript c stands for countries - our unit of analysis, *GovtResponse* is the policy response stringency index as measured in each country; *Confidence* is the index of confidence in others and in institutions observed in 2016; X is the vector of control variables mentioned in Section 5.3 that allows us to account for possible confounding factors that may affect governments' policy decisions. Finally, ε is the error term.

To check whether less stringent policies adopted in high trust contexts are more or less effective to prevent mortality and limit the spread of the infection, we regress the index of confidence, and its alternative specifications, on three measures of the effectiveness of countermeasures to the pandemics: the speed of decline of new contagions, the number of new positive cases and the number of new deaths due to Covid-19. In all cases we estimate the same linear model, as follows:

$$Y_c = \alpha + \gamma_1 \cdot Confidence_c + \gamma_2 \cdot Z_c + \epsilon_c \tag{5.2}$$

where Y is the dependent variable (alternatively, the speed of decline of new contagions, mortality rate, and new positive cases); the subscript c stands for countries; *Confidence* is the index of confidence in others and in institutions; Z is a vector of control variables that includes the logarithm of GDP per capita, the Gini index, the expected number of life years free from chronic diseases, the government response stringency one week before the peak of new infections, a dichotomous variable identifying countries with young democracies, and ϵ is the error term. We control for the government response stringency because it can limit new contagions and deaths independently from the degree of confidence in others and in institutions.

To test the robustness of our findings, we run various specifications of equations 5.1 and 5.2 in which we alternatively remove the dummy for young democracies, include a dummy for Eastern European countries, account for people's frequency of social contacts, and try various specifications of the index of confidence. All variables in the estimated models have been standardised for comparability in the interpretation of the estimated coefficients sizes.

5.4 Results

During the first wave of Covid-19, countries with high trust in others and institutions (in 2016) introduced, on average, less stringent policies than others (see Figure 5.1). The correlation coefficient between the two variables is -0.51 (significant at 1%). This result holds after controlling for GDP per capita, income inequality, mortality before the lockdown, the number of beds available in intensive care units, the expected number of life years with chronic disease, and a dummy for countries with young democracies (see Model 2 of Table 5.1).

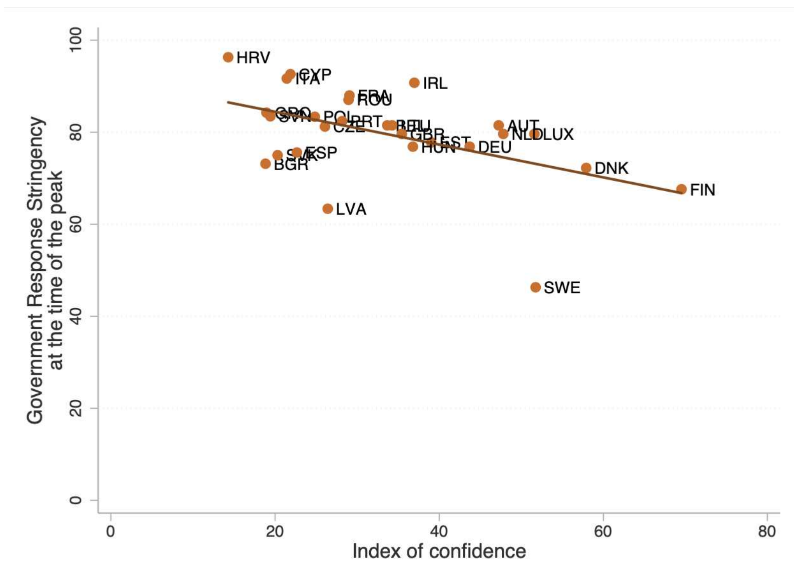

Figure 5.1: Countries where trust in others and institutions is high adopted less stringent policies.

(a) Source: own elaboration of data from Oxford Covid-19 Government Response Tracker (OxCGRT) and the 2016 wave of the European Quality of Life Study (EQLS).

This result is rather robust to changes in the list of control variables. For instance, the control for the share of people that rarely meet others, is not statistically significant and its inclusion does not change the relationship between trust and policy stringency (Model 3). Also, our result does not depend on the inclusion of a dummy for countries with young democracies or for Eastern European countries (Model 5), although Model 2 (which controls for young democracies) performs better in terms of explained variance ($R^2 = 35\%$).

One may argue that the policy stringency of a country does not depend on its GDP per capita (not statistically significant in Model 2), but on its public debt/GDP ratio. In other words, countries' expenditure to contain the epidemics may be constrained by their financial exposure relative to GDP, rather than by GDP. Model 5 shows that our result does not change if we control for the public debt/GDP ratio: its coefficient is statically insignificant, while the magnitude and significance of the index of confidence remains negative and significant.

The last three columns of Table 5.1 show the sensitiveness of our result to different specifications of the index of confidence. In Model 7 we include an index based on trust in others, in the government and in the parliament; in Model 8 we consider an index based only on trust in government and in the parliament; in Model 9 we use only the share of people who declare to trust others. In short, the higher the trust in a country, the less stringent are the adopted policies: the coefficients of the alternative specifications of the index of confidence are somewhat smaller than the one from Model 2, but they retain their sign and significance.

The evidence that governments of high-trust countries introduced less stringent policies to face Covid-19 does not imply that these countries were more effective in facing the epidemic. Milder policies may have translated into more contagions and deaths. To account for this possibility, we consider three additional outcome variables: the speed of decline of contagions, and the number of new deaths and new positive cases. Results are available in Table 5.2.

The coefficients of the index of confidence are negative and statistically significant for all three variables: ceteris paribus, higher trust correlates with faster decline of new contagions after the peak (Model 1 of Table 5.2), less new deaths (Model 5 of Table 5.2), and less new positive cases (Model 9 of Table 5.2). These relationships are sensitive to different specifications of the index of confidence (see rows 7 to 9): the coefficients have the expected (negative) sign, but they are not always statistically significant. This is mainly the case of trust in others (row 9). Summarizing, our results suggest that countries where trust is high faced the epidemics with less freedom limitations, faster, and with less fatalities. This conclusion is robust to the inclusion of various control variables, and various specifications of the index of confidence.

Table 5.1: Association between the index of confidence and government response stringency after controls. Results are robust to various specifications of the index of confidence and to the inclusion of a varied list of control variables.

	Policy Stringency								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Index of confidence	-0.274**	-0.474***	-0.423***	-0.429**	-0.429**	-0.421**			
	(-2.68)	(-3.88)	(-4.00)	(-3.52)	(-3.50)	(-2.93)			
GDP per capita in 2018 (constant 2010 US Dollars, log)		0.0543	-0.0373	0.504	0.344		0.101	0.0744	0.0495
		(0.14)	(-0.09)	(1.39)	(0.56)		(0.27)	(0.19)	(0.12)
Gini index		0.149	-0.0314	0.145	0.0913	0.0982	0.0784	0.0482	0.171
		(0.73)	(-0.12)	(0.73)	(0.35)	(0.42)	(0.45)	(0.28)	(0.82)
Total deaths before the lockdown (x 1 million)		-0.0707	-0.0460	0.0102	-0.000161	-0.0672	-0.0583	-0.0177	-0.0984
		(-0.53)	(-0.43)	(0.10)	(-0.00)	(-0.48)	(-0.47)	(-0.16)	(-0.63)
Total number of ICU beds (x 100,000)		0.0898	0.143	0.129	0.138	0.111	0.0538	0.125	-0.0487
		(1.13)	(1.29)	(1.58)	(1.37)	(1.01)	(0.67)	(1.60)	(-0.47)
Average number of life years with chronic disease		0.185	0.161	0.162	0.163	0.172	0.137	0.133	0.147
		(1.23)	(1.17)	(1.10)	(1.08)	(1.20)	(1.01)	(1.00)	(0.93)
Young democracies		-0.555*	-0.476			-0.491	-0.546*	-0.427	-0.627*
		(-1.80)	(-1.38)			(-1.41)	(-1.88)	(-1.47)	(-1.83)
Share of people who meet rarely			-0.159						
			(-1.21)						
Eastern European countries					-0.148				
					(-0.40)				
Public debt as a share of GDP (2019)						0.0766			
						(0.75)			
Index of confidence$_1$							-0.493***		
							(-3.99)		
Index of confidence$_2$								-0.473***	
								(-4.14)	
Trust in others									-0.456**
									(-3.08)
Constant	0.179*	0.523	0.426	-0.168	-0.00750	0.494	0.423	0.350	0.599
	(1.83)	(0.98)	(0.71)	(-0.50)	(-0.01)	(1.45)	(0.85)	(0.69)	(1.06)
Observations	27	27	27	27	27	27	27	27	27
Adjusted R^2	0.212	0.311	0.350	0.288	0.255	0.326	0.338	0.362	0.176

Note: OLS estimates with robust standard errors. t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

Table 5.2: Association between the index of confidence and three measures of efficacy in facing the epidemic: speed of decline of new contagion and the number of new deaths and new contagions at the peak.

	Decline of contagions after the peak				New Deaths				Positive Cases			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Index of confidence	-0.873**				-0.773*				-0.169*			
	(-2.61)				(-1.74)				(-1.85)			
GDP per capita in 2018 (constant 2010 US dollars, log)	0.0916	0.461	0.501	0.164	1.187	1.805	1.774	1.504	2.242***	2.257***	2.209***	2.309***
	(0.05)	(0.26)	(0.32)	(0.07)	(0.61)	(0.98)	(0.99)	(0.78)	(4.09)	(4.07)	(3.91)	(4.42)
Gini index	0.0686	-0.0279	0.0178	0.0781	-0.137	-0.280	-0.315	-0.111	0.620**	0.589**	0.607**	0.586**
	(0.18)	(-0.06)	(0.04)	(0.17)	(-0.16)	(-0.29)	(-0.35)	(-0.11)	(3.12)	(2.90)	(2.79)	(3.17)
Government response stringency one week before the peak	-0.0470	0.00421	-0.0266	0.120	-0.381				-0.136	-0.138	-0.129	-0.138
	(-0.19)	(0.02)	(-0.11)	(0.46)	(-1.02)				(-1.34)	(-1.35)	(-1.29)	(-1.39)
Expected number of life years with chronic disease	-0.0362	-0.109	-0.148	-0.0415	-0.321	-0.409	-0.413	-0.401	-0.0354	-0.0533	-0.0532	-0.0523
	(-0.19)	(-0.49)	(-0.65)	(-0.19)	(-1.29)	(-1.62)	(-1.59)	(-1.68)	(-0.55)	(-0.90)	(-0.87)	(-0.83)
Eastern European countries	-0.903	-0.721	-0.600	-0.664	-1.653	-1.029	-1.079	-0.832	0.461	0.462	0.495	0.463
	(-1.04)	(-0.81)	(-0.72)	(-0.63)	(-0.88)	(-0.60)	(-0.67)	(-0.46)	(1.13)	(1.12)	(1.16)	(1.19)
Index of confidence$_1$		-0.854**				-0.658				-0.175*		
		(-2.56)				(-1.53)				(-1.86)		
Index of confidence$_2$			-0.815**				-0.745*				-0.133	
			(-2.91)				(-1.88)				(-1.28)	
Trust in others				-0.691				-0.309				-0.201**
				(-1.36)				(-0.69)				(-2.42)
Constant	0.393	-0.103	-0.227	0.365	0.134	-0.416	-0.400	-0.113	-1.648**	-1.688**	-1.641**	-1.733**
	(0.21)	(-0.05)	(-0.13)	(0.15)	(0.06)	(-0.20)	(-0.20)	(-0.05)	(-3.25)	(-3.32)	(-3.23)	(-3.44)
Observations	19	19	19	19	27	27	27	27	27	27	27	27
R^2	0.466	0.461	0.488	0.305	0.332	0.294	0.325	0.238	0.789	0.790	0.780	0.797

Note: OLS estimates with robust standard errors. t statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.

5.5 Conclusion

During the first wave of Covid-19, the extent to which governments' containment policies relied on voluntary compliance or on restrictions of social and economic activity, showed substantial international variability. What explains such cross-country differences? This is a critical question because economic and psychological costs of an epidemic surge with the severity of restrictions. In the light of the increased risk of epidemics characterizing recent decades, it is crucial to understand what allows a country to contain infections while imposing mild restrictions on its population. To date, the available evidence is limited, suggesting only that autocracies introduced more stringent lockdowns than democracies (Frey et al., 2020).

Governments' emphasis on the importance of social capital for the outcomes of containment policies suggests a possible role of social capital in shaping their policy choice. In high social capital countries, governments may anticipate wide voluntary compliance, thus leaning towards non-stringent measures. The opposite can happen in countries with low social capital. However, the relationship between social capital and policy choice remained inconclusive so far.

We provide quantitative evidence that pre-existing levels of trust in others and in institutions are negatively related to governments' policy stringency in response to Covid-19 in 27 European Union member States. This did not happen at the expense of public health: holding policy stringency constant, high trust countries report lower mortality, as well as lower number and faster decline of new contagions than others.

Our results refer to the first wave of the Covid-19 pandemic and they are robust to several specifications of the measure of trust in others and institutions, and to a number of control variables. We accounted for countries' gross domestic product (per capita), their income inequality, as well as a measure of the size of their population burdened with chronic diseases. Additionally, we accounted for countries' health infrastructure and the severity of the epidemics. Our findings are also independent of the frequency of face-to-face interactions. Such frequency is a source of trust (Soroka et al., 2003), but also an amplifier of infections. Thus, it is possible that countries with preexisting high levels of trust are also characterised by high frequency of face-to-face meetings and, therefore, fast spread of the infection. However, this does not seem to be the case: the coefficient of our measure of trust retains its sign, significance and magnitude when we control for the frequency of social gatherings which, on the contrary, does not attract a statistically significant coefficient. Moreover, our results do not change if we control for the public debt/GDP ratio of a country, rather than its gross domestic product.

The fact that the coefficients of most of our controls are non-significant should not suggest their lack of relation with the dependent variable. Coefficients have the expected signs and their non-significance may depend on the low numerosity of our sample. For instance, it is difficult to think that the availability of beds in intensive care units did not play a role, given the emphasis of all governments on the need to avoid the collapse of the healthcare system. However, the robustness of our results suggests that the social context affects government' s strategies more than the other factors we control for. In summary, our results suggest that the answer to the question whether epidemics impose a trade-off between freedom and health depends on the level of trust prevalent in a country: the more people trust others and institutions, the more the trade-off fades.

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Chapter 6

Conclusions

6.1 Main findings and contribution to the literature

In this thesis, I explored the effects of social capital for measures of subjective wellbeing and public health using an empirical approach. In particular, I employed various measures of social capital and of subjective wellbeing, a variety of datasets which allowed for a comparison of social capital and wellbeing measures within and across countries; and used both parametric and non-parametric methods to analyse subjective wellbeing. Overall, results are consistent across chapters in confirming the commonly found positive effect of social capital for wellbeing, and its maintenance in times of crisis. In particular, the analyses reveal that social capital operates to promote wellbeing in various ways: at the individual level, it reduces the importance of income and social comparisons for wellbeing (Chapter 2), as well as it guarantees resilience by fostering values and sense of belonging in times of crisis (Chapter 3); at the macro-level, it relates to lower wellbeing inequality between rich and poor people (Chapter 2). My results also show that the positive effects of social capital are not limited to life satisfaction and mental health, but extend to public health and governance outcomes. In fact, I show that in countries with high social capital, governments imposed less stringent lockdown policies to face the Covid-19 pandemic, but also had fewer infection cases, a lower number of deaths and had a faster decline in the number of contagions (Chapter 5). Additionally, evidence shows that the lack of social capital, measured as loneliness, increases the probability of individuals' suffering (Chapter 4).

This thesis contributes to the wider literature on social capital and wellbeing, in particular in the context of a health crisis. I tackle two main research questions: firstly, if social capital is effective in reducing the negative consequences of social comparisons for individuals' subjective wellbeing; and secondly, I test whether social capital is effective at easing the limitations to relational freedom imposed by the pandemic and their negative consequences for wellbeing. The answer to these questions is that social capital is key for both.

Specifically, I bring two contributions: firstly, I explore the moderating impact that social capital exerts in the income-wellbeing and social comparisons-wellbeing relationships from an economic point of view. As stated in Chapter 2, few researchers have explored this relationship in depth, and our contribution is to check for endogeneity issues, widen the data scope of the analysis and relate the results to a macro-level implication. Indeed, given that micro-level results show that social capital reduces the importance of income and status achievements for wellbeing, at the macro-level this contributes to decreasing the wellbeing gap between rich and poor people. The second main contribution I bring is on the operationalisation of social capital for wellbeing in times of a health crisis. Results from Chapter 3 suggest that social capital affects wellbeing in at least two ways: firstly, via in-person activities and engagement with social networks, and secondly, via the value that social networks leave within people, which make up for the feelings of belongingness and trust that people have. Then, when the Covid-19 crisis hit, the imposed social distancing affected at least one of the two pathways, as people were required not to socially gather. The expectation would be that people with high social capital suffered from this imposed reduction in social activities, however results suggest that they were better-off than people with low social capital. This is strong evidence that social capital is a factor that influences wellbeing even when people are unable to socially interact. Additionally my contribution pertains to the social capital and public health and governance literature: results from Chapter 5 suggest that societies with higher social capital faced the pandemic better, with fewer deaths and infections, as well as with relatively more freedom.

Throughout this thesis I have analysed *individual level* social capital, that is, the quality and quantity of social relations that people reportedly have, and their trust in others and institutions. It may be argued that *how much* social capital people have is up to their own decision. It is a choice of people how much to interact with others, whether to be trusting of others or if to volunteer and donate to charities. In the utility function of individuals, when evaluating what matters to their wellbeing, they will allocate a certain value to social capital. However, there are many positive consequences of having high social capital rates in societies, among which higher levels of happiness, and according to the findings in this thesis, lower wellbeing inequality and good public health outcomes. Investing in social capital policies to maintain the current levels of, or increase social capital will ultimately favour those who care for it the most, but it will also create positive externalities for the society as a whole. Building societies in which social capital is encouraged, where interpersonal connections are facilitated and collaborative attitudes are prevalent will ultimately increase wellbeing and quality of life that everyone will enjoy, not only those who care for social capital more.

Overall, this thesis emphasises the importance of social capital in promoting subjective wellbeing and public health. I emphasise the key role that social capital plays for reducing limitations to personal relational freedoms, and how to limit these limitations' negative consequences for individuals' wellbeing in the context of a health crisis. These findings are timely in a world in which the likeliness of infectious diseases is increasing. Additionally, my findings also show that social capital mitigates the importance of social comparisons. This is relevant because social comparisons that seem to be on the rise, they negatively contribute to individuals' subjective wellbeing, they hamper the possibilities of growth to contribute to happiness growth, and increases the disparities in the wellbeing distribution.

The evidence reported here has hence important policy implications, suggesting that policies to promote social capital are feasible and necessary. Policies to promote social capital are crucial for reducing the wellbeing gap between rich and poor people and for mitigating the negative effects of health crises, such as the Covid-19 pandemic, as well as for maintaining and promoting individuals' wellbeing.

In the context of an increasingly complex world, with lower reported wellbeing and life satisfaction, increased mental illnesses, and decreasing levels of social capital, studying wellbeing can help to rethink priorities and reappraise goals for societies. This thesis contributes to this growing body of research by examining the determinants of subjective wellbeing and identifying interventions that promote wellbeing, which include policies for social capital.

Appendix A

Chapter 2 Appendix

Table A.1: VIF Test

	EU-SILC	ESS	WVS-EVS	SOEP
Social capital = 1	2.46	1.67	1.72	3.25
Social capital = 2	2.76	1.87	2	3.33
Social capital = 3				1.98
Social capital = 4				1.29
individual income	12.33	6.05	1.56	341
reference income	303.53		1.43	402.04
income rank 1-3		2.82		
income rank 8-10		1.73		

Note: The high collinearity on the income and reference income should not cause any concern, as it is a mechanical consequence of the construction of the reference income variable.

A.1 European Union Statistics on Income and living conditions (EU-SILC)

Table A.2: OLS with robust standard errors using EU-SILC (2013) data: detailed results.

	(1)		(2)		(3)	
	Life Sat.		Life Sat.		Life Sat.	
Social capital index = 1	1.168***	(0.0317)	-0.304***	(0.0151)	0.960***	(0.0582)
Social capital index = 2	2.154***	(0.0342)	-0.447***	(0.0163)	1.842***	(0.0599)
Log of individual income	0.511***	(0.0195)	-0.156***	(0.00883)	0.675***	(0.0422)
Social capital index = 1 * Log of individual income	-0.0806***	(0.0218)	0.0582***	(0.00992)	-0.268***	(0.0454)
Social capital index = 2 * Log of individual income	-0.241***	(0.0208)	0.0911***	(0.00959)	-0.392***	(0.0440)
Log of reference income	-0.158***	(0.0352)	0.105***	(0.0181)	-0.397***	(0.0636)
Social capital index = 1 * Log of reference income	0.0442**	(0.0220)	-0.0589***	(0.00996)	0.213***	(0.0457)
Social capital index = 2 * Log of reference income	0.148***	(0.0211)	-0.101***	(0.00970)	0.276***	(0.0443)
Female	0.105***	(0.00674)	0.122***	(0.00350)	0.0487***	(0.0102)
26-35	-0.311***	(0.0170)	0.105***	(0.00870)	-0.0342	(0.0254)
36-45	-0.521***	(0.0176)	0.156***	(0.00894)	-0.0169	(0.0255)
46-55	-0.704***	(0.0183)	0.188***	(0.00931)	-0.0471*	(0.0268)
Above 55	-0.565***	(0.0188)	0.111***	(0.00957)	-0.00232	(0.0279)
Married	0.405***	(0.00960)	-0.0842***	(0.00501)	0.194***	(0.0131)
Widowed	-0.00154	(0.0156)	0.0541***	(0.00799)	0.160***	(0.0387)
Divorced or separated	-0.0894***	(0.0146)	0.0608***	(0.00747)	0.168***	(0.0207)
has disability	-0.578***	(0.00751)	0.302***	(0.00390)	-0.305***	(0.0131)
Secondary education	0.131***	(0.0122)	-0.0734***	(0.00622)	0.0448	(0.0307)
Tertiary education	0.294***	(0.0137)	-0.113***	(0.00698)	0.172***	(0.0316)
Unemployed	-0.861***	(0.0153)	0.314***	(0.00752)		
Student	0.308***	(0.0178)	0.000981	(0.00915)		
Retired	0.0373***	(0.0112)	-0.0237***	(0.00577)		
Not working	-0.231***	(0.0123)	0.119***	(0.00630)		
House owner	0.143***	(0.00796)	-0.0443***	(0.00409)	-0.00360	(0.0127)
Constant	4.399***	(0.224)	2.612***	(0.120)	5.082***	(0.367)
Number of observations	317978		317978		152095	
Adjusted R^2	0.315		0.171		0.120	

Notes: Dependent variable: Life satisfaction (0-10). Depressed = frequency of feeling depressed or downhearted (1-5). Job Sat. = Job satisfaction (1-10).
Omitted categories: "Social capital index = 0", "Social capital index = 0 * log of individual income", "Social capital index = 0 * log of reference income".
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parenthesis.

Table A.3: Correlations table

	Getting together with friends	individual income	Trust in others	reference income	SCindex
Getting together with friends	1				
individual income	0.2463*	1			
Trust in others	0.1398*	0.1156*	1		
reference income	0.1890*	0.9496*	0.0883*	1	
SCindex	0.7243*	0.2342*	0.7840*	0.1793*	1

Table A.4: Robustness check using the single dummies for social capital rather than the index (EU-SILC, 2013)

	Life Satisfaction		Depression		Job satisfaction	
	(1)	(2)	(3)	(4)	(5)	(6)
	Getting together with friends	Trust in others	Getting together with friends	Trust in others	Getting together with friends	Trust in others
SC	1.224***	1.193***	-0.240***	-0.265***	0.999***	1.074***
	(0.0268)	(0.0258)	(0.0127)	(0.0117)	(0.0457)	(0.0424)
Log of individual income	0.493***	0.616***	-0.146***	-0.165***	0.623***	0.569***
	(0.0142)	(0.0116)	(0.00633)	(0.00506)	(0.0286)	(0.0191)
SC * Log of individual income	-0.121***	-0.277***	0.0590***	0.0786***	-0.268***	-0.222***
	(0.0157)	(0.0134)	(0.00705)	(0.00603)	(0.0304)	(0.0224)
Log of reference income	-0.109***	-0.172***	0.0793***	0.0704***	-0.303***	-0.256***
	(0.0333)	(0.0320)	(0.0173)	(0.0167)	(0.0562)	(0.0518)
SC * Log of reference income	0.0533***	0.213***	-0.0616***	-0.0775***	0.190***	0.150***
	(0.0160)	(0.0139)	(0.00720)	(0.00623)	(0.0309)	(0.0230)
Constant	4.623***	4.476***	2.568***	2.672***	5.117***	5.265***
	(0.228)	(0.227)	(0.121)	(0.120)	(0.369)	(0.366)
Controls (socio-demographic, country)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	317978	317978	317978	317978	152095	152095
Adjusted R^2	0.285	0.294	0.156	0.160	0.102	0.111

Note: OLS with robust standard errors. Dependent variable: Life satisfaction (0-10). Depressed = frequency of feeling depressed or downhearted (1-5). Job Sat. = Job satisfaction (1-10). Controls: sex, age group, marital status, education level, labour market status, house owner, long standing illness or disability, country dummies. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard Errors in parenthesis.

Table A.5: Descriptive statistics (EU-SILC, 2013): micro-data

	count	mean	sd	min	max
Life satisfaction	317978	6.939401	2.133051	0	10
Depressed (1-5)	317978	2.039849	1.004411	1	5
Job satisfaction (0-10)	152095	7.245071	2.053106	0	10
Individual income	317978	1140.575	1260.038	0	110438.8
Log of individual income	317978	6.159619	1.909749	0	11.61223
Reference income	317978	1135.363	766.3204	1.982637	3120.429
Log of reference income	317978	6.308553	1.828514	1.092808	8.046046
Getting together with friends	317978	.734142	.4417897	0	1
Trust in others	317978	.5772695	.4939941	0	1
Social capital index (0-2)	317978	1.311411	.706143	0	2
Social capital index = 0	317978	.142101	.3491543	0	1
Social capital index = 1	317978	.4043865	.4907737	0	1
Social capital index = 2	317978	.4535125	.497835	0	1
Female	317978	.5506702	.4974267	0	1
Under 26	317978	.0961828	.2948422	0	1
26-35	317978	.1259112	.3317498	0	1
36-45	317978	.1682443	.3740837	0	1
46-55	317978	.1891389	.3916195	0	1
Above 55	317978	.4205228	.4936437	0	1
Single	317978	.2459069	.4306243	0	1
Married	317978	.5671807	.495467	0	1
Widowed	317978	.0973338	.2964122	0	1
Divorced or separated	317978	.0895785	.2855774	0	1
has disability	317978	.352603	.4777812	0	1
Primary education or no education	317978	.1260024	.3318526	0	1
Secondary education	317978	.6277101	.4834158	0	1
Tertiary education	317978	.2462875	.4308486	0	1
Working	317978	.4758914	.4994192	0	1
Unemployed	317978	.0754926	.264185	0	1
Student	317978	.0545352	.2270711	0	1
Retired	317978	.2779029	.447966	0	1
Not working	317978	.1161778	.3204386	0	1
House owner	317978	.5581235	.4966109	0	1

Table A.6: Lewbel EU-SILC

	(1) LifeSat
Social Capital index	0.443*
	(0.248)
Social capital * individual income	-0.795***
	(0.251)
Social capital * reference income	0.810***
	(0.260)
Individual income	1.401***
	(0.327)
Reference income	-1.112***
	(0.332)
Female	0.102***
	(0.00689)
26-35	-0.313***
	(0.0179)
36-45	-0.515***
	(0.0197)
46-55	-0.698***
	(0.0212)
Above 55	-0.553***
	(0.0216)
Married	0.398***
	(0.0104)
Widowed	-0.0292
	(0.0183)
Divorced or separated	-0.0929***
	(0.0152)
Secondary Education	0.113***
	(0.0137)
Tertiary Education	0.325***
	(0.0255)
Unemployed	-0.809***
	(0.0272)
Student	0.301***
	(0.0191)
Retired	0.00461
	(0.0165)
Not working	-0.227***
	(0.0144)
House Owner	0.138***
	(0.00920)
has disability or longstanding illness	-0.591***
	(0.0124)
Constant	5.228***
	(0.340)
N	317978
Adjusted R^2	0.296
Hansen Statistic	1.844
p-value	01745
First step F test: Social Capital	180.76
First step F test: Social Capital * individual income	64.21
First step F test: Social Capital * reference income	65.32
Kleibergen-Paap Wald F test	32.55
Endogeneity test p-value	0.000

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Descriptive statistics: EU-SILC (2013), country level data.

	count	mean	sd	min	max
LS gap between 1st and 5th income quintile	29	1.410001	.5166415	.6524148	2.65728
Share of people with SC index =2	29	.4673399	.1544134	.1987608	.7739409
Gini index	29	30.20345	4.033652	22.7	38
GDP per capita	29	27.17931	12.49118	10.1	70.5

Table A.8: Descriptive statistics: EU-SILC (2013), regional level data.

	count	mean	sd	min	max
LS gap between 1st and 5th income quintile	99	1.260262	.4147933	.2247949	2.717926
Share of people with SC index =2	99	.4644989	.1273024	.1529882	.7739409
Gini index	99	.2954481	.0362704	.2300008	.4260471
GDP per capita	99	24.79495	8.545059	9.3	70.5

Table A.9: Robustness check of country level analysis on EU-SILC (2013) data using the 50/10 ratio as a measure of income inequality.

	Difference in life satisfaction between rich and poor		
	(1)	(2)	(3)
Share of people with SC = 2	-0.502**	-0.615***	-0.591***
	(0.160)	(0.130)	(0.144)
Gini	0.291		
	(0.149)		
GDP per capita (log)	-0.109	-0.109	-0.0600
	(0.129)	(0.136)	(0.129)
50/10 share		0.273	
		(0.138)	
50/10 cut-off			0.305
			(0.189)
N	29	28	28

Note: Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: The unit of analysis are countries. All coefficients are standardised for comparability. Data for Gini, 50/10 ratio and GDP are from Eurostat. Share refers to share of national equivalised income and cut-off refers to the top cut-off point. All variables are standardised for comparability.

Table A.10: Robustness check of regional level analysis on EU-SILC (2013) data using the 50/10 ratio as a measure of income inequality.

	Difference in life satisfaction between rich and poor		
	(1)	(2)	(3)
Share of people with SC = 2	-0.498***	-0.571***	-0.583***
	(0.101)	(0.114)	(0.112)
Gini	0.241*		
	(0.112)		
GDP per capita (log)	0.0191	0.0165	0.0596
	(0.0701)	(0.0783)	(0.0746)
50/10 share		0.116	
		(0.0906)	
50/10 cut-off			0.178
			(0.103)
N	99	97	97

Note: Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: The unit of analysis are countries. All coefficients are standardised for comparability. Data for Gini, 50/10 ratio and GDP are from Eurostat. Share refers to share of national equivalised income and cut-off refers to the top cut-off point. All variables are standardised for comparability.

Table A.11: Robustness check of country level analysis on EU-SILC (2013) data using the 90/10 ratio as a measure of income inequality.

	Difference in life satisfaction between rich and poor		
	(1)	(2)	(3)
Share of people with SC = 2	-0.502**	-0.614***	-0.552**
	(0.160)	(0.124)	(0.155)
Gini	0.291		
	(0.149)		
GDP per capita (log)	-0.109	-0.0282	-0.0475
	(0.129)	(0.108)	(0.112)
90/10 share		0.361*	
		(0.141)	
90/10 cut-off			0.349
			(0.177)
N	29	28	28

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The unit of analysis are regions. All coefficients are standardised for comparability. Data for Gini, 90/10 ratio and GDP are from Eurostat. Share refers to share of national equivalised income and cut-off refers to the top cut-off point.
All variables are standardised for comparability.

Table A.12: Robustness check of regional level analysis on EU-SILC (2013) data using the 90/10 ratio as a measure of income inequality.

	(1)	(2)	(3)
Share of people with SC = 2	-0.498***	-0.593***	-0.577***
	(0.101)	(0.112)	(0.107)
Gini	0.241*		
	(0.112)		
GDP per capita (log)	0.0191	0.0490	0.0748
	(0.0701)	(0.0734)	(0.0663)
90/10 share		0.171	
		(0.0935)	
90/10 cut-off			0.205*
			(0.0977)
N	99	97	97

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The unit of analysis are regions. All coefficients are standardised for comparability. Data for Gini, 90/10 ratio and GDP are from Eurostat. Share refers to share of national equivalised income and cut-off refers to the top cut-off point.
All variables are standardised for comparability.

A.2 European Social Survey (ESS)

Table A.13: OLS with robust standard errors using ESS (2018) data: detailed results.

	(1) Life satisfaction (0-10)		(2) Happiness (0-10)	
Social capital index = 1	1.808***	(0.388)	2.629***	(0.363)
Social capital index = 2	3.227***	(0.417)	3.520***	(0.381)
Income rank 1-3	-0.161**	(0.0696)	-0.0804	(0.0637)
Income rank 8-10	0.156**	(0.0623)	0.105*	(0.0555)
Social capital index = 1 * Income rank 1-3	0.0102	(0.0802)	-0.0713	(0.0727)
Social capital index = 1 * Income rank 8-10	-0.0665	(0.0702)	-0.110*	(0.0625)
Social capital index = 2 * Income rank 1-3	0.191**	(0.0824)	0.0615	(0.0747)
Social capital index = 2 * Income rank 8-10	-0.120*	(0.0693)	-0.134**	(0.0618)
Household income	0.529***	(0.0484)	0.491***	(0.0456)
Social capital index = 1 * Household income	-0.153***	(0.0505)	-0.261***	(0.0473)
Social capital index = 2 * Household income	-0.274***	(0.0537)	-0.327***	(0.0492)
Sex (1=male)	-0.0886***	(0.0198)	-0.140***	(0.0178)
Age	-0.0548***	(0.00399)	-0.0450***	(0.00358)
Age squared (divided by 100)	0.0521***	(0.00398)	0.0397***	(0.00359)
Years of education	0.0179***	(0.00265)	0.0127***	(0.00238)
Unemployed	-0.698***	(0.0577)	-0.368***	(0.0523)
Student	0.218***	(0.0493)	0.205***	(0.0444)
Retired	0.00551	(0.0380)	-0.0851**	(0.0340)
Not working	-0.0260	(0.0440)	-0.0266	(0.0381)
Living with partner	0.438***	(0.0251)	0.591***	(0.0225)
Has children	0.0856***	(0.0281)	0.129***	(0.0251)
Permanently sick or disabled	-0.980***	(0.0746)	-0.716***	(0.0656)
Constant	3.573***	(0.402)	3.801***	(0.377)
Number of observations	38597		38597	
Adjusted ^{2}	0.253		0.221	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.
Note: Dependent variables: Life Satisfaction (1-10), Happiness (1-10).
Omitted categories: "Income rank 4-7", "Social Capital index = 0 * Log of household income" and "Social Capital index = 0 * income rank 4-7". Included controls are also country dummies

Table A.14: Robustness check using the single dummies of social capital rather than the index (ESS 2018).

	(1) Life satisfaction (0-10)	(2) Life satisfaction (0-10)	(3) Happiness (0-10)	(4) Happiness (0-10)
Meeting socially		1.921***		2.655***
		(0.311)		(0.289)
Social trust	1.797***		1.520***	
	(0.301)		(0.276)	
Household income	0.459***	0.516***	0.347***	0.464***
	(0.0366)	(0.0405)	(0.0341)	(0.0380)
Income rank 1-3	-0.151***	-0.166***	-0.142***	-0.0769
	(0.0481)	(0.0554)	(0.0436)	(0.0506)
Income rank 8-10	0.131***	0.140***	0.0611*	0.0419
	(0.0396)	(0.0440)	(0.0357)	(0.0394)
Social trust * Household income	-0.146***		-0.125***	
	(0.0385)		(0.0353)	
Meeting socially * Household income		-0.180***		-0.276***
		(0.0399)		(0.0371)
Social trust * Income rank 1-3	0.117**		0.110**	
	(0.0594)		(0.0534)	
Social trust * Income rank 8-10	-0.0828*		-0.100**	
	(0.0468)		(0.0420)	
Meeting socially * Income rank 1-3		0.0776		-0.0587
		(0.0635)		(0.0574)
Meeting socially * Income rank 8-10		-0.0818		-0.0469
		(0.0504)		(0.0450)
Controls (socio-demographic, country)	Yes	Yes	Yes	Yes
Number of observations	38597	38597	38597	38597
Adjusted R^2	0.239	0.233	0.202	0.203

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: OLS with robust standard errors
Controls: sex, age, age squared, living with partner, having children, years of education, permanently sick or disabled, labour market status, country dummies.

Table A.15: ESS: Correlations Table

	Meeting socially	Social trust	Income rank	Household income	Social capital index
Meeting socially	1				
Social trust	0.1032*	1			
Income rank	0.0661*	0.1282*	1		
Household income	0.1250*	0.2284*	0.7220*	1	
Social capital index	0.7393*	0.7460*	0.1309*	0.2382*	1

Table A.16: Lewbel ESS

	(1)
	LS
Social capital index	-0.305
	(0.971)
Social Capital * Household income	0.0788
	(0.105)
Social Capital * Income rank 1-3	1.339**
	(0.603)
Social Capital * Income rank 8-10	-0.205
	(0.424)
Household income	0.293***
	(0.113)
Income rank 1-3	-1.430**
	(0.606)
Income rank 8-10	0.349
	(0.481)
Female	0.0911***
	(0.0205)
Age	-0.0532***
	(0.00425)
Age squared (divided by 100)	0.0510***
	(0.00420)
Child	0.0771***
	(0.0289)
Unemployed	-0.683***
	(0.0592)
Student	0.190***
	(0.0537)
Retired	0.00810
	(0.0386)
Not working	-0.0126
	(0.0449)
Years of education	0.0166***
	(0.00318)
Permanently sick or disabled	-0.966***
	(0.0763)
Partner	0.453***
	(0.0273)
Constant	5.474***
	(1.018)
Number of observations	38597
Adjusted R^2	0.223
Hansen Statistic	2.614
p-value	0.6243
First step F test: Social Capital	11.36
First step F test: Social Capital * individual income	17.38
First step F test: Social Capital * income rank 1-3	9.95
First step F test: Social Capital * income rank 8-10	10.45
Kleibergen-Paap Wald F test	6.19
Endogeneity test p-value	0.0282

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Additional controls are country dummies.

Table A.17: Descriptive statistics (ESS 2018).

	count	mean	sd	min	max
Life satisfaction (0-10)	38597	7.14698	2.177084	0	10
Happiness (0-10)	38597	7.456875	1.912693	0	10
Household income (EUR, EU28=100)	38597	7.527611	.8426338	4.839056	9.718941
Income rank 1-3	38597	.318859	.4660403	0	1
Income rank 4-7	38597	.4230122	.4940437	0	1
Income rank 8-10	38597	.2581289	.4376109	0	1
Social trust	38597	.4467446	.4971622	0	1
Meeting socially	38597	.6038293	.489107	0	1
Social capital index (0-2)	38597	1.050574	.7342374	0	2
Social capital index = 0	38597	.2455372	.4304108	0	1
Social capital index = 1	38597	.4583517	.4982689	0	1
Social capital index = 2	38597	.2961111	.4565465	0	1
Female	38597	.5303262	.4990859	0	1
Age	38597	51.90593	18.06593	15	90
Age squared (divided by 100)	38597	30.20594	18.83742	2.25	81
Years of education	38597	13.09444	4.191266	0	60
Permanently sick or disabled	38597	.0337073	.180477	0	1
Working	38597	.5205068	.4995858	0	1
Unemployed	38597	.0477498	.2132392	0	1
Student	38597	.0529834	.2240032	0	1
Retired	38597	.2871208	.4524243	0	1
Not working	38597	.0916392	.2885198	0	1
Living with partner	38597	.5968858	.4905297	0	1

Table A.18: Detailed results of the country level analysis using ESS (2018) data.

	Life Satisfaction gap between rich and poor			
	(1)	(2)	(3)	(4)
Share of people with SC index =2	-0.626***			-0.286
	(0.132)			(0.215)
Gini index (std.)		0.474**		0.203
		(0.176)		(0.137)
GDP per capita (log)			-0.647***	-0.327
			(0.166)	(0.243)
Number of observations	29	29	29	29
Adjusted R^2	0.370	0.195	0.397	0.425

Standard errors in parentheses

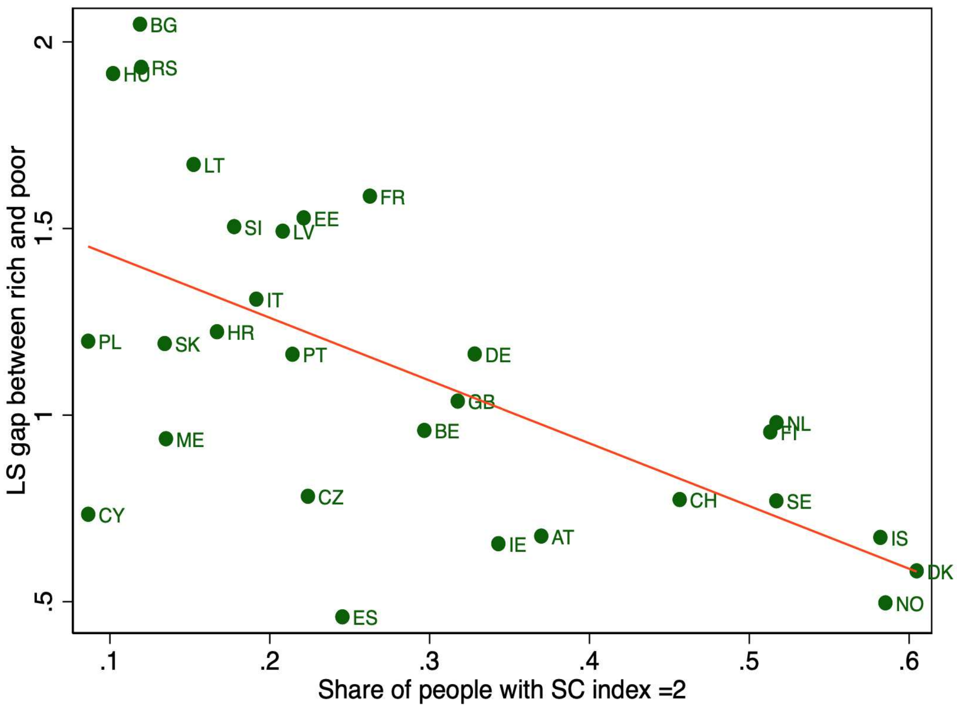
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The unit of analysis are countries.
Data for Gini are from Eurostat, data for GDP are from the World Bank.
All variables are standardised for comparability.

Table A.19: Descriptive statistics: ESS (2018), country level data.

	count	mean	sd	min	max
LS gap between rich and poor	29	1.117328	.4446341	.4594297	2.047614
Social capital index (0-2)	29	.2854172	.1656544	.0863853	.6047104
Gini index (Eurostat)	29	29.50345	4.512798	20.9	39.6
GDP per capita, PPP	29	10.6571	.3377325	9.978005	11.34935

Figure A.1: Across European countries, the life satisfaction gap between rich and poor people negatively correlates with social capital (ESS, 2018).



Note: Social capital is measured as the share of respondents with a social capital index = 2.

Table A.20: Robustness check of country level analysis on ESS (2018) data using the 90/10 ratio as a measure of income inequality.

	Difference in life satisfaction between rich and poor		
	(1)	(2)	(3)
Share of people with SC = 2	-0.286	-0.182	-0.162
	(0.215)	(0.175)	(0.184)
Gini	0.203		
	(0.137)		
GDP per capita (log)	-0.327	-0.544^{**}	-0.552^{**}
	(0.243)	(0.175)	(0.172)
90/10 share4		0.219^{*}	
		(0.0894)	
90/10 cut-off 4			0.179
			(0.192)
N	29	27	27

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The unit of analysis are countries.
Data for Gini and 90/10 ratios are from Eurostat, data for GDP are from the World Bank.
Share refers to share of national equivalised income and cut-off refers to the top cut-off point.
All variables are standardised for comparability.

Table A.21: Robustness check of country level analysis on ESS (2018) data using the 50/10 ratio as measure of income inequality.

	Difference in life satisfaction between rich and poor		
	(1)	(2)	(3)
Share of people with SC = 2	-0.286	-0.188	-0.172
	(0.215)	(0.176)	(0.184)
Gini	0.203		
	(0.137)		
GDP per capita (log)	-0.327	-0.555**	-0.561**
	(0.243)	(0.180)	(0.180)
50/10 share		0.206*	
		(0.0775)	
50/10 cut-off			0.157
			(0.191)
N	29	27	27

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The unit of analysis are countries.
Data for Gini and 50/10 ratios are from Eurostat, data for GDP are from the World Bank.
Share refers to share of national equivalised income and cut-off refers to the top cut-off point.
All variables are standardised for comparability.

A.3 Integrated European Values Study - World Values Study (WVS-EVS)

Table A.22: OLS with robust standard errors using WVS-EVS (waves 3-6) data: detailed results.

	(1) Life satisfaction		(2) Happiness	
Social capital index = 1	-0.0636	(0.123)	-0.00946	(0.0404)
Social capital index = 2	0.235*	(0.126)	0.0834**	(0.0424)
Social class (subjective)	-0.381***	(0.0238)	-0.103***	(0.00785)
Social capital index = 1 * Social class (subjective)	0.125***	(0.0282)	0.0277***	(0.00928)
Social capital index = 2 * Social class (subjective)	0.197***	(0.0292)	0.0393***	(0.00983)
Scale of incomes	0.108***	(0.00895)	0.0179***	(0.00299)
Social capital index = 1 * Scale of incomes	-0.0210**	(0.0105)	-0.00383	(0.00347)
Social capital index = 2 * Scale of incomes	-0.0583***	(0.0106)	-0.00968***	(0.00360)
female	0.133***	(0.0172)	0.0538***	(0.00571)
age	-0.0451***	(0.00351)	-0.0168***	(0.00115)
age squared /100	0.0475***	(0.00369)	0.0149***	(0.00121)
Completed (compulsory) elementary education	0.0612	(0.0542)	0.00853	(0.0172)
Incomplete secondary school: technical/vocational type/(Comp	0.151**	(0.0613)	0.0468**	(0.0194)
Complete secondary school: technical/vocational type/Seconda	0.0975*	(0.0546)	0.0332*	(0.0173)
Incomplete secondary: university-preparatory type/Secondary,	0.155***	(0.0595)	0.0265	(0.0188)
Complete secondary: university-preparatory type/Full seconda	0.00783	(0.0559)	0.00657	(0.0179)
Some university without degree/Higher education - lower-leve	-0.0383	(0.0581)	-0.0146	(0.0186)
University with degree/Higher education - upper-level tertia	0.0515	(0.0557)	-0.0117	(0.0178)
x007r==divorced/separated	-0.643***	(0.0343)	-0.225***	(0.0114)
x007r==widowed	-0.471***	(0.0438)	-0.234***	(0.0146)
x007r==single	-0.481***	(0.0281)	-0.180***	(0.00948)
x028r==Part time	-0.0914***	(0.0282)	-0.000732	(0.00947)
x028r==Self employed	-0.0826**	(0.0330)	0.00475	(0.0108)
x028r==Retired	-0.0328	(0.0346)	-0.000170	(0.0114)
x028r==Housewife	0.0246	(0.0328)	0.00837	(0.0105)
x028r==Students	0.0792**	(0.0394)	0.00950	(0.0132)
x028r==Unemployed	-0.583***	(0.0425)	-0.152***	(0.0138)
x028r==Other	-0.318***	(0.0677)	-0.0470**	(0.0218)
one child	-0.0304	(0.0296)	0.0111	(0.00995)
two children	-0.00231	(0.0272)	0.0205**	(0.00924)
three children	0.0523*	(0.0296)	0.0502***	(0.00997)
Constant	8.071***	(0.179)	3.854***	(0.0590)
Controls (socio-demographic, country)	Yes		Yes	
Number of observations	48849		49973	
Adjusted R^2	0.147		0.121	

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: Dependent variables: Life satisfaction (1-10). Happiness (1-4).
Omitted categories: "Social capital index = 0", "Social capital index = 0 * household income", "Social capital index = 0 * social class".
Included controls are also country and year dummies.

Table A.23: Robustness check using individual dummies of social capital (WVS-EVS, Waves 3-6)

	(1) Life satisfaction	(2) Life satisfaction	(3) Happiness	(4) Happiness
Household income	0.0999***	0.0952***	0.0163***	0.0167***
	(0.00557)	(0.00700)	(0.00183)	(0.00233)
Social class	-0.311***	-0.343***	-0.0902***	-0.0900***
	(0.0146)	(0.0192)	(0.00479)	(0.00630)
Trust in others	0.296***		0.0646*	
	(0.0888)		(0.0297)	
Trust in others*Social class	0.104***		0.0250***	
	(0.0206)		(0.00688)	
Trust in others*Household income	-0.0472***		-0.00702**	
	(0.00732)		(0.00247)	
Putnam's group		-0.0182		0.0385
		(0.0980)		(0.0324)
Putnam's group*social class		0.102***		0.0138
		(0.0227)		(0.00750)
Putnam's group*Household income		-0.0177*		-0.00394
		(0.00815)		(0.00272)
Constant	8.077***	8.088***	3.855***	3.842***
	(0.157)	(0.167)	(0.0513)	(0.0548)
N	49647	49838	50770	50960
Adjusted R^2	0.144	0.139	0.118	0.115

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: OLS with robust standard errors. Dependent variables: Life satisfaction (1-10). Happiness (1-4).
Omitted categories: "Social capital index = 0", "Social capital index = 0 * household income", "Social capital index = 0 * social class".
Controls: sex, age, age squared, education, marital status, number of children, labour market status, country and year dummies.

Table A.24: Lewbel WVS-EVS

	(1)
	a170r
Social Capital index	-0.625
	(0.813)
Social capital index * individual income	-0.0222
	(0.0749)
Social capital index * social class	0.334*
	(0.195)
Social class	-0.613***
	(0.204)
Individual income	0.106
	(0.0882)
female	0.130***
	(0.0179)
age	-0.0440***
	(0.00359)
age squared /100	0.0464***
	(0.00387)
Completed (compulsory) elementary education	0.0351
	(0.0597)
Incomplete secondary school: technical/vocational type	0.110*
	(0.0664)
Complete secondary school: technical/vocational type	0.0545
	(0.0744)
Incomplete secondary: university-preparatory type	0.109
	(0.0802)
Complete secondary: university-preparatory type	-0.0295
	(0.104)
Some university without degree/Higher education	-0.0680
	(0.137)
University with degree/Higher education	0.0337
	(0.163)
divorced/separated	-0.644***
	(0.0408)
widowed	-0.473***
	(0.0442)
single	-0.484***
	(0.0290)
Part-time	-0.0883***
	(0.0314)
Self-employed	-0.0853**
	(0.0335)
Retired	-0.0329
	(0.0472)
Housewife	0.0292
	(0.0337)
Student	0.0821
	(0.0564)
Unemployed	-0.558***
	(0.0549)
Other	-0.312***
	(0.0720)
one child	-0.0348
	(0.0327)
two children	0.000497
	(0.0291)
three children	0.0558
	(0.0375)
Constant	10.04***
	(0.884)
Number of observations	48849
Adjusted R^2	0.140
Hansen Statistic	4.402
p-value	0.2212
First step F test: Social Capital	14.40
First step F test: Social Capital * individual income	11.17
First step F test: Social Capital * reference income	16.08
Kleibergen-Paap Wald F test	3.63
Endogeneity test p-value	0.3110

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.25: Correlations table

	social class	household income	SCindex	putnam's group	trust in others
social class	1				
household income	-0.4573*	1			
SCindex	-0.1044*	0.1300*	1		
putnam's group	-0.0758*	0.0849*	0.7628*	1	
trust in others	-0.0694*	0.1011*	0.7009*	0.0734*	1

Table A.26: Descriptive statistics (WVS-EVS, Waves 3-6)

variable	obs	mean	sd	min	max
life satisfaction	87177	7.349	1.930	1	10
happiness	86649	3.212	0.640	1	4
female	87113	0.531	0.499	0	1
age	86877	47.32	17.48	15	108
age squared /100	86877	25.44	17.45	2.250	116.6
Inadequately completed elementary education	84189	0.0396	0.195	0	1
Completed (compulsory) elementary education	84189	0.135	0.341	0	1
Incomplete secondary school: technical/vocational type	84189	0.115	0.319	0	1
Complete secondary school: technical/vocational type	84189	0.142	0.349	0	1
Incomplete secondary: university-preparatory type	84189	0.102	0.303	0	1
Complete secondary: university-preparatory type	84189	0.172	0.378	0	1
Some university without degree/Higher education	84189	0.124	0.330	0	1
University with degree/Higher education	84189	0.171	0.377	0	1
married	86659	0.614	0.487	0	1
divorced/separated	86659	0.0841	0.277	0	1
widowed	86659	0.0700	0.255	0	1
single	86659	0.232	0.422	0	1
Full-time	86444	0.408	0.491	0	1
Part-time	86444	0.0941	0.292	0	1
Self-employed	86444	0.0621	0.241	0	1
Retired	86444	0.205	0.404	0	1
Housewife	86444	0.0979	0.297	0	1
Students	86444	0.0551	0.228	0	1
Unemployed	86444	0.0539	0.226	0	1
no child	56256	0.306	0.461	0	1
Other	86444	0.0239	0.153	0	1
one child	56256	0.147	0.354	0	1
two children	56256	0.303	0.460	0	1
three children	56256	0.244	0.429	0	1
Social class (subjective)	53168	3.111	0.897	1	5
Scale of incomes	52912	5.073	2.413	1	10
trust in others	84755	0.406	0.491	0	1
membership in at least 1 Putnam's group	85240	0.575	0.494	0	1
Social capital index (0-2)	82941	0.985	0.751	0	2
Year survey	87177	2006	5.178	1994	2014
Country/region	87177	439.4	255.0	20	909

Table A.28: Descriptive statistics: WVS-EVS (waves 3-6), country level data.

	count	mean	sd	min	max
Life satisfaction	60	1.318469	.734709	-.2658081	3.233333
Share of people with SC index = 2	63	.2800295	.1679835	.0134298	.658322
GDP per capita (log)	63	10.64228	.3476524	9.86037	11.59522
Gini	63	31.67036	4.306507	23.25295	44.24099
Year survey	63	-	-	1994	2014

Table A.27: Detailed results of the country level analysis using WVS-EVS (waves 3-6) data.

	Difference in life satisfaction between rich and poor			
	(1)	(2)	(3)	(4)
Share of people with SC index = 2	-0.153*			-0.149
	(0.0726)			(0.0967)
Gini index		0.233		0.00153
		(0.203)		(0.249)
Gdp per capita (log)			-0.476	-0.0391
			(0.273)	(0.338)
Number of observations	60	60	60	60
Adjusted R^2	0.199	0.115	0.132	0.160

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: OLS with robust standard errors. The unit of analysis are countries.
All variables are standardised for comparability.

Table A.29: List of developed countries included in the analysis of WVS-EVS (waves 3-6) data.

Andorra	Germany	Malta	United Kingdom
Australia	Greece	Netherlands	United States
Austria	Hong	New	
Belgium	Iceland	Norway	
Canada	Ireland	Portugal	
Taiwan	Italy	Singapore	
Cyprus	Japan	Spain	
Finland	South	Sweden	
France	Luxembourg	Switzerland	

Table A.30: Robustness check of country level analysis on EVS-WVS data using the 90/10 ratio as a measure of income inequality

	Difference in life satisfaction between rich and poor	
	(1)	(2)
Share of people with SC = 2	-0.149	-0.131
	(0.0967)	(0.143)
Gdp per capita (log)	-0.0391	0.00434
	(0.338)	(0.578)
gini	0.00153	
	(0.249)	
90/10		0.105
		(0.418)
N	60	40

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: The unit of analysis are countries. Data for Gini, 90/10 and for GDP are from the World Bank. Share refers to share of national equivalised income and cut-off refers to the top cut-off point.
All variables are standardised for comparability.

A.4 German Socio Economic Panel (SOEP)

Table A.33: Correlations table

	Social capital index	Soc Gath Monthly	Help Fre Monthly	Volunt Monthly	Local participation	Individual income	Reference income
Social capital index	1						
Soc Gath Monthly	0.6045*	1					
Help Fre Monthly	0.6901*	0.3067*	1				
Volunt Monthly	0.6553*	0.1027*	0.1470*	1			
Local participation	0.4886*	0.0295*	0.0745*	0.3701*	1		
Individual income	0.1046*	0.0851*	-0.0273*	0.1326*	0.0888*	1	
Reference income	0.0463*	0.0123*	-0.0297*	0.0987*	0.0443*	0.2464*	1

Table A.31: OLS with robust standard errors and individual fixed effects using SOEP data: detailed results.

	(1) Life Satisfaction	
Social capital index = 1	-0.995	(0.835)
Social capital index = 2	-1.960**	(0.874)
Social capital index = 3	-1.619	(1.041)
Social capital index = 4	-1.933	(1.424)
Log of individual income	0.474***	(0.0413)
Social capital index = 1 * Log of individual income	-0.0824**	(0.0401)
Social capital index = 2 * Log of individual income	-0.127***	(0.0425)
Social capital index = 3 * Log of individual income	-0.207***	(0.0481)
Social capital index = 4 * Log of individual income	-0.248***	(0.0632)
Log of reference income	-0.698***	(0.145)
Social capital index = 1 * Log of reference income	0.246**	(0.115)
Social capital index = 2 * Log of reference income	0.429***	(0.121)
Social capital index = 3 * Log of reference income	0.466***	(0.143)
Social capital index = 4 * Log of reference income	0.550***	(0.199)
Age	-0.0139***	(0.00478)
Age squared (divided by 100)	-0.0106**	(0.00460)
Married	0.132***	(0.0315)
Widowed	-0.131**	(0.0624)
Divorced/Separated	0.0245	(0.0471)
Years of education	-0.0139*	(0.00739)
Unemployed	-0.591***	(0.0287)
Student	0.0813**	(0.0403)
Retired	0.0271	(0.0313)
Non working	-0.0310	(0.0195)
House owner	0.0663***	(0.0208)
East Germany	-0.288**	(0.135)
Disability Status of Individual	-0.289***	(0.0315)
Constant	9.434***	(1.050)
Controls (socio-demographic, region, year)	Yes	
Individual fixed effects	Yes	
Number of observations	129901	
Number of individuals	36599	
R^2 within	0.0390	
R^2 between	0.0636	
R^2 overall	0.0585	

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Omitted categories: "Social capital index = 0 * log of individual income", "Social capital index = 0 * log of reference income".
Controls: regional dummies, year dummies.
We note that the main effect of social capital becomes negative when the estimation includes the interaction term between reference income and social capital.
We do not have an explanation for that, hence we suggest further research on this topic.

Table A.32: Robustness check using the single dummies for social capital rather than the index (SOEP).

	(1) Social gathering	(2) Helping friends	(3) Performing volunteer work	(4) Participation in local politics
SC	-1.376**	-0.702	-0.311	-1.470*
	(0.680)	(0.533)	(0.616)	(0.877)
Log of individual income	0.455***	0.408***	0.403***	0.377***
	(0.0362)	(0.0240)	(0.0245)	(0.0223)
SC × Log of individual income	-0.115***	-0.0848***	-0.114***	-0.0610
	(0.0334)	(0.0250)	(0.0272)	(0.0395)
Log of reference income	-0.658***	-0.480***	-0.467***	-0.448***
	(0.131)	(0.112)	(0.113)	(0.109)
SC × Log of reference income	0.331***	0.193***	0.161*	0.259**
	(0.0939)	(0.0744)	(0.0861)	(0.124)
Constant	9.270***	8.475***	8.437***	8.482***
	(0.946)	(0.804)	(0.805)	(0.778)
Controls (socio-demographic, region, year)	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
Number of observations	129901	129901	129901	129901
Number of individuals	36599	36599	36599	36599
R^2 within	0.0388	0.0358	0.0347	0.0344
R^2 between	0.0622	0.0527	0.0502	0.0491
R^2 overall	0.0575	0.0491	0.0471	0.0462

Note: OLS with individual fixed effects and robust standard errors.
Dependent variable: Life satisfaction (0-10). Controls: sex (omitted due to fixed effects), age, age squared, marital status, years of education, labour market status, house owner, disability status of individual, living in East Germany, regional dummies, year dummies.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Standard errors in parentheses.

Table A.34: Correlations table

	Social capital index	Soc Gath Monthly	Help Fre Monthly	Volunt Monthly	Local participation	Individual income	Reference income
Social capital index	1						
Soc Gath Monthly	0.6045*	1					
Help Fre Monthly	0.6901*	0.3067*	1				
Volunt Monthly	0.6553*	0.1027*	0.1470*	1			
Local participation	0.4886*	0.0295*	0.0745*	0.3701*	1		
Individual income	0.1046*	0.0851*	-0.0273*	0.1326*	0.0888*	1	
Reference income	0.0463*	0.0123*	-0.0297*	0.0987*	0.0443*	0.2464*	1

Table A.35: Descriptive statistics (SOEP).

	count	mean	sd	min	max
Life satisfaction	129901	6.918122	1.783707	0	10
Individual income (2011 EUR)	129901	1732.723	1027.361	0	44728.43
Log of individual income	129901	7.341583	.4721802	0	10.70839
Reference income (2011 EUR)	129901	1724.819	249.5303	1192.22	2243.969
Log of reference income	129901	7.443037	.1444213	7.084411	7.716447
Soc Gath Monthly	129901	.7748593	.4176765	0	1
Help Fre Monthly	129901	.4126373	.4923105	0	1
Volunt Monthly	129901	.2890124	.4533054	0	1
Local participation	129901	.090569	.2869963	0	1
Social capital index (0-4)	129901	1.567078	1.0297	0	4
Social capital index = 0	129901	.1552875	.3621799	0	1
Social capital index = 1	129901	.3352784	.4720895	0	1
Social capital index = 2	129901	.335671	.4722263	0	1
Social capital index = 3	129901	.1345948	.3412916	0	1
Social capital index = 4	129901	.0391683	.1939959	0	1
Age	129901	47.77856	17.12055	16	101
Age squared (divided by 100)	129901	25.75902	17.28232	2.56	102.01
Single	129901	.2156334	.4112626	0	1
Married	129901	.6354378	.481309	0	1
Widowed	129901	.0660349	.2483441	0	1
Divorced or separated	129901	.0828939	.2757228	0	1
Years of education	129901	11.81008	2.652272	7	18
Working	129901	.585977	.4925544	0	1
Unemployed	129901	.0557501	.2294395	0	1
Student	129901	.0240568	.1532261	0	1
Retired	129901	.171777	.3771879	0	1
Not working	129901	.1624391	.3688545	0	1
House owner	129901	.4866552	.4998238	0	1
East Germany	129901	.2652328	.4414588	0	1
Baden-Wuerttemberg	129901	.1240175	.3296028	0	1
Bavaria	129901	.1362191	.3430224	0	1
Berlin	129901	.0385986	.1926371	0	1
Brandenburg	129901	.0447341	.2067202	0	1
Bremen	129901	.0069976	.083359	0	1
Hamburg	129901	.0133948	.1149587	0	1
Hesse	129901	.0694452	.2542107	0	1
Mecklenburg-Western Pomeran	129901	.0269513	.1619417	0	1
Lower Saxony	129901	.085288	.2793109	0	1
North Rhine-Westphalia	129901	.1971578	.397854	0	1
Rhineland-Palatinate	129901	.0495454	.2170047	0	1
Saarland	129901	.0063279	.0792963	0	1
Saxony	129901	.079576	.2706367	0	1
Saxony-Anhalt	129901	.0472129	.2120947	0	1
Schleswig-Holstein	129901	.0260275	.1592177	0	1
Thuringia	129901	.0485062	.2148341	0	1
1992	129901	.0884751	.2839857	0	1
1994	129901	.0849339	.2787844	0	1
1996	129901	.0855652	.2797219	0	1
1997	129901	.0838177	.2771153	0	1
1999	129901	.0986982	.2982576	0	1
2005	129901	.1443869	.3514829	0	1
2007	129901	.1440559	.3511477	0	1
2009	129901	.1416309	.3486726	0	1
2011	129901	.1284363	.3345762	0	1
Has disability	129901	.1117389	.3150462	0	1

Table A.36: Lewbel SOEP

	(1) LifeSat
Social Capital index	-4.019**
	(1.811)
Social capital * individual income	-0.0910
	(0.245)
Social capital * reference income	0.642***
	(0.197)
Individual income	0.506
	(0.378)
Reference income	-1.364***
	(0.315)
Female	0
	(.)
Age	-0.0166***
	(0.00447)
Age squared	-0.00837*
	(0.00434)
Married	0.126***
	(0.0291)
Widowed	-0.129**
	(0.0544)
Divorced/Separated	0.0226
	(0.0430)
Years of education	-0.0145**
	(0.00667)
Unemployed	-0.589***
	(0.0269)
Student	0.0777**
	(0.0386)
Retired	0.0294
	(0.0285)
Non working	-0.0289
	(0.0182)
House Owner	0.0687***
	(0.0201)
East Germany	-0.291***
	(0.127)
Has disability	-0.287***
	(0.0289)
N	119701
Adjusted R^2	-0.237
Hansen Statistic	9.608
p-value	0.3831
First step F test: Social Capital	11.18
First step F test: Social Capital * individual income	3.70
First step F test: Social Capital * reference income	63.13
Kleibergen-Paap Wald F test	3.06
Endogeneity test p-value	0.04

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.5 Error Propagation method

We estimate the errors of our moderation effects using the error propagation method.

Formally, the formula for the error propagation method is defined as follows: let $f(x_1, x_2, ..., x_n)$ be a function which depends on n variables $x_1, ..., x_n$ and the the uncertainty around each variable be defined as $x_i \pm \Delta x_i$, where Δx_i is the error.

If the variables are correlated, the function error Δf is calculated as follows

$$\Delta f = \sqrt{\sum_{i=1}^{n} \sum_{k=1}^{n} (\frac{\delta f}{\delta x_i} \frac{\delta f}{\delta x_k} C_{i,k})}$$

where $C_{i,k}$ is the covariance between the couples of variables, $C_{i,k} = cov(x_i, x_k)$.

In our case, the function is the moderation effect, which is defined as the ratio between the estimated coefficients on the interaction term of social capital with income (reference or absolute), and income. In particular:

$$f = \frac{SC * Income}{Income}$$

where income is either absolute income or reference income, and both terms in the ratio are the estimated coefficients from the equation of well-being on social capital, income and reference income and their interaction (Table 1 in the main document), which we assume are correlated.

After some computation the formula to obtain the errors on the moderation effect can be written as follows:

$$S.E. = \sqrt{\frac{(se_{SC*Inc})^2}{Income^2} + \frac{(SC * Income)^2}{Income^4} \times (se^2_{Inc}) - 2\frac{SC * Income}{(Income)^2} \frac{1}{Income} C_{SC*Inc,Inc}}$$

where se stands for standard error of the incomes and interaction coefficients, and the rest are all estimated coefficients. $C_{SC*Inc,Inc}$ is the covariance between estimated coefficients.

Appendix B

Chapter 3 Appendix

B.1 GHQ

Variable	GHQ-12 Composition
Concentration	Have you recently been able to concentrate on whatever you're doing? 1. Better than usual 2. Same as usual 3. Less than usual 4. Much less than usual
Loss of Sleep	Have you recently lost much sleep over worry? 1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual
Playing a useful role	Have you recently felt that you were playing a useful part in things? 1. More so than usual 2. Same as usual 3. Less so than usual 4. Much less than usual
Capable of making decisions	Have you recently felt capable of making decisions about things? 1. More so than usual 2. Same as usual 3. Less so than usual 4. Much less capable
Constantly under strain	Have you recently felt constantly under strain? 1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual
Problem overcoming difficulties	Have you recently felt you couldn't overcome your difficulties? 1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual
Enjoy day-to-day activities	Have you recently been able to enjoy your normal day-to-day activities? 1. More so than usual 2. Same as usual 3. Less so than usual 4. Much less than usual
Ability to face problems	Have you recently been able to face up to problems? 1. More so than usual 2. Same as usual 3. Less able than usual 4. Much less able
Unhappy or depressed	Have you recently been feeling unhappy or depressed? 1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual
Losing confidence	Have you recently been losing confidence in yourself? 1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual
Believe worthless	Have you recently been thinking of yourself as a worthless person? 1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual
General happiness	Have you recently been feeling reasonably happy, all things considered? 1. More so than usual 2. About the same as usual 3. Less so than usual 4. Much less than usual

B.2 Social capital

Social capital proxy	Questions
Social Network support	
Friends	How much can you open up to friends if you need to talk about your worries? 1. A lot, 2. somewhat, 3. a little, 4. not at all - Collected in wave 5 (2013-2015)
	How much can you rely on them if you have a serious problem? 1. A lot, 2. somewhat, 3. a little, 4. not at all. - Collected in wave 5 (2013-2015)
Personal relations	
Belong to neighbourhood	Here are some statements about neighbourhoods. Please answer how strongly you agree or disagree with each statement. I feel like I belong to this neighbourhood. 1. Strongly agree 2. agree 3. neither agree nor disagree 4. disagree 5. strongly disagree - Collected in wave 9 (2017-2019)
Talk to neighbourhood	Please answer how strongly you agree or disagree with each statement. I regularly stop and talk with people in my neighbourhood. 1. Strongly agree 2. agree 3. neither agree nor disagree 4. disagree 5. strongly disagree - Collected in wave 9 (2017-2019)
Civic Engagement	
Putnam groups	Whether you are a member or not, do you join in the activities of any of these organisations on a regular basis? Organisations: church or religious group, volunteering groups and scouts group. 1. yes, 0. no - Collected in wave 9 (2017-2019)
Trust and cooperative norms	
Trust in neighbours	People in this neighbourhood can be trusted. 1. Strongly agree 2. agree 3. neither agree nor disagree 4. disagree 5. strongly disagree - Collected in wave 6 (2014-2016)
Help from neighbours	People around here are willing to help their neighbours. 1. Strongly agree 2. agree 3. neither agree nor disagree 4. disagree 5. strongly disagree - Collected in wave 6 (2014-2016)

Table B.1: Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Pidp	-	-	-	-	48148
Wave	-	-	1	10	48148
GHQ	11.568	5.498	0	36	48148
Life satisfaction	5.053	1.496	1	7	37582
Social Network Support:	0.466	0.499	0	1	48148
Personal Relations	0.288	0.453	0	1	48148
Civic Participation	0.233	0.423	0	1	48148
Trust and Cooperative Norms	0.198	0.398	0	1	48148
Female	0.574	0.495	0	1	48148
Age	57.812	13.465	19	94	48148
Age squared	3523.538	1521.782	361	8836	48148
couple	0.737	0.44	0	1	48148
London	0.082	0.275	0	1	47895
Wales	0.045	0.208	0	1	47895
Scotland	0.079	0.27	0	1	47895
North Ireland	0.03	0.171	0	1	47895
Household composition	1.529	1.204	0	10	48148
Quintile 1	0.2	0.4	0	1	48148
Quintile 2	0.194	0.395	0	1	48148
Quintile 3	0.202	0.401	0	1	48148
Quintile 4	0.202	0.401	0	1	48148
Quintile 5	0.203	0.402	0	1	48148
Employed	0.504	0.5	0	1	48148
Self-employed	0.076	0.265	0	1	48148
Unemployed	0.4	0.49	0	1	48148
Both employed and self-employed	0.02	0.139	0	1	48148
GCSE	0.24	0.427	0	1	48148
BA	0.37	0.483	0	1	48148
Diploma	0.126	0.332	0	1	48148
A levels	0.095	0.293	0	1	48148
No education	0.169	0.375	0	1	48148
Has health condition	0.53	0.499	0	1	48148
At risk of contracting Covid	0.061	0.24	0	1	48137
British white	0.902	0.298	0	1	47432
Irish	0.013	0.112	0	1	47432
Other white	0.025	0.155	0	1	47432
Mixed	0.011	0.103	0	1	47432
Black	0.014	0.117	0	1	47432
BIP	0.026	0.159	0	1	47432
Chinese or Asian	0.009	0.096	0	1	47432
Arab	0.001	0.035	0	1	47432

Notes: The number of observations is on a subset of the sample that has non missing information on GHQ, the social capital variables, age, gender, employment, income and education, and who have lived in the same neighbourhood since 2015. The life satisfaction row has a lower number of observations as the question was asked less frequently.

Table B.2: Correlations table

	GHQ	1.	2.	3.	4.
GHQ	1				
1. Social Network support	-0.0155*	1			
2. Personal Relations	-0.0826*	0.0961*	1		
3. Civic Participation	-0.0282*	0.0390*	0.0821*	1	
4. Trust Cooperative norms	-0.0345*	0.0884*	0.2384*	0.0535*	1

B.3 Full tables of results

Table B.3: GHQ regressions on social capital

	(1) Friends	(2) Personal Relations	(3) Putnam Groups	(4) Trust and Cooperative
	Can rely on and open up to friends	Belonging to and talking to neighbours	Active member of Putnam's groups	Can trust and get help from neighbours
April20	1.184***	1.281***	1.389***	1.342***
	(0.106)	(0.0919)	(0.0908)	(0.0878)
May20	1.168***	1.179***	1.247***	1.265***
	(0.103)	(0.0890)	(0.0880)	(0.0851)
June20	1.265***	1.272***	1.314***	1.375***
	(0.103)	(0.0916)	(0.0890)	(0.0872)
July20	0.758***	0.693***	0.796***	0.785***
	(0.101)	(0.0900)	(0.0876)	(0.0855)
September20	0.968***	0.913***	1.014***	1.017***
	(0.104)	(0.0905)	(0.0899)	(0.0857)
November20	1.645***	1.640***	1.712***	1.829***
	(0.109)	(0.0956)	(0.0954)	(0.0918)
January21	1.813***	1.782***	1.937***	1.900***
	(0.121)	(0.109)	(0.110)	(0.105)
March21	1.396***	1.361***	1.470***	1.486***
	(0.111)	(0.0961)	(0.0957)	(0.0926)
Sep21	1.011***	0.936***	0.978***	1.032***
	(0.111)	(0.0982)	(0.0955)	(0.0927)
SC=1	-0.740***	-0.969***	-0.202	-0.274*
	(0.125)	(0.136)	(0.142)	(0.156)
April20 × SC=1	0.542***	0.542***	0.191	0.482**
	(0.151)	(0.170)	(0.176)	(0.194)
May20 × SC=1	0.325**	0.486***	0.310*	0.279
	(0.146)	(0.162)	(0.168)	(0.184)
June20 × SC=1	0.341**	0.528***	0.472***	0.253
	(0.149)	(0.163)	(0.174)	(0.185)
July20 × SC=1	0.154	0.481***	0.146	0.240
	(0.145)	(0.159)	(0.168)	(0.181)
September20 × SC=1	0.296**	0.671***	0.398**	0.459**
	(0.148)	(0.165)	(0.170)	(0.195)
November20 × SC=1	0.432***	0.712***	0.573***	0.0994

	(0.155)	(0.172)	(0.173)	(0.195)
January21 × SC=1	0.337**	0.683***	0.131	0.371*
	(0.156)	(0.175)	(0.176)	(0.203)
March21 × SC=1	0.285*	0.584***	0.257	0.224
	(0.157)	(0.175)	(0.178)	(0.197)
Sep21 × SC=1	0.0709	0.377**	0.281	0.0696
	(0.154)	(0.168)	(0.178)	(0.193)
Controls				
Female	1.422***	1.422***	1.422***	1.422***
	(0.111)	(0.111)	(0.111)	(0.111)
Age	-0.0394	-0.0336	-0.0365	-0.0385
	(0.0262)	(0.0262)	(0.0262)	(0.0262)
age2	-0.000423*	-0.000477**	-0.000450*	-0.000431*
	(0.000240)	(0.000241)	(0.000240)	(0.000240)
Living with a partner	-0.124	-0.108	-0.110	-0.121
	(0.132)	(0.132)	(0.132)	(0.132)
London	1.960***	1.953***	1.988***	1.966***
	(0.530)	(0.530)	(0.525)	(0.528)
Wales	0.136	0.131	0.134	0.135
	(0.257)	(0.257)	(0.257)	(0.257)
Scotland	-0.0797	-0.0784	-0.0754	-0.0796
	(0.202)	(0.202)	(0.202)	(0.202)
NorthIre	0.0317	0.0305	0.0196	0.0260
	(0.318)	(0.318)	(0.318)	(0.318)
Household size	-0.0133	-0.0149	-0.0138	-0.0135
	(0.0578)	(0.0578)	(0.0577)	(0.0577)
quintile 2	0.0105	0.0154	0.0129	0.0159
	(0.0747)	(0.0746)	(0.0746)	(0.0748)
quintile 3	-0.0735	-0.0683	-0.0759	-0.0671
	(0.0768)	(0.0768)	(0.0767)	(0.0769)
quintile 4	0.0332	0.0397	0.0329	0.0385
	(0.0825)	(0.0823)	(0.0825)	(0.0825)
quintile 5	-0.0431	-0.0368	-0.0445	-0.0407
	(0.0925)	(0.0924)	(0.0925)	(0.0926)
self-employed	-0.0846	-0.0746	-0.0866	-0.0837
	(0.160)	(0.160)	(0.160)	(0.160)
unemployed	0.0201	0.0356	0.0129	0.0239
	(0.103)	(0.103)	(0.103)	(0.103)
both emp and sel-empl.	0.319	0.325	0.301	0.311
	(0.355)	(0.355)	(0.356)	(0.355)
BA or higher	0.200	0.203	0.201	0.202

	(0.146)	(0.146)	(0.146)	(0.146)
Diploma or equivalent	0.305	0.307	0.305	0.307
	(0.188)	(0.188)	(0.188)	(0.188)
A Level or equivalent	-0.0257	-0.0198	-0.0231	-0.0229
	(0.206)	(0.206)	(0.206)	(0.206)
No education	-0.151	-0.147	-0.152	-0.151
	(0.169)	(0.169)	(0.169)	(0.169)
Has health condition	0.912***	0.914***	0.913***	0.912***
	(0.109)	(0.109)	(0.109)	(0.109)
NHS shielded patient	0.877***	0.873***	0.874***	0.878***
	(0.210)	(0.210)	(0.210)	(0.210)
Irish	1.093**	1.091**	1.096**	1.097**
	(0.537)	(0.538)	(0.537)	(0.537)
Other White	-0.00217	-0.00620	-0.00512	-0.00243
	(0.340)	(0.340)	(0.340)	(0.340)
Mixed	1.257**	1.256**	1.254**	1.255**
	(0.584)	(0.585)	(0.584)	(0.584)
Black	-0.304	-0.305	-0.293	-0.301
	(0.530)	(0.531)	(0.530)	(0.530)
BIP	0.277	0.278	0.281	0.275
	(0.390)	(0.390)	(0.389)	(0.390)
Chinese or Asian	-0.00415	-0.00347	0.00406	0.00310
	(0.558)	(0.558)	(0.558)	(0.558)
Arab	1.229	1.200	1.210	1.205
	(1.827)	(1.832)	(1.829)	(1.826)
mean couple	-0.872***	-0.891***	-0.885***	-0.874***
	(0.212)	(0.212)	(0.212)	(0.212)
mean London	-1.579***	-1.577***	-1.608***	-1.587***
	(0.558)	(0.558)	(0.554)	(0.557)
mean hhcomposition	0.0376	0.0395	0.0375	0.0383
	(0.0839)	(0.0839)	(0.0838)	(0.0839)
mean quintile 2	-0.781***	-0.785***	-0.785***	-0.787***
	(0.289)	(0.289)	(0.289)	(0.289)
mean quintile 3	-0.785***	-0.791***	-0.785***	-0.792***
	(0.281)	(0.281)	(0.281)	(0.281)
mean quintile 4	-1.312***	-1.318***	-1.310***	-1.317***
	(0.282)	(0.282)	(0.282)	(0.282)
mean quintile 5	-1.530***	-1.538***	-1.529***	-1.534***
	(0.273)	(0.273)	(0.273)	(0.273)
mean both	-0.423	-0.435	-0.403	-0.419
	(0.497)	(0.497)	(0.497)	(0.496)

mean selfemployed	0.522*	0.512*	0.529*	0.522*
	(0.277)	(0.277)	(0.277)	(0.277)
mean unemployed	0.631***	0.627***	0.645***	0.629***
	(0.217)	(0.218)	(0.217)	(0.217)
Social Network Support		-0.472***	-0.474***	-0.473***
		(0.110)	(0.110)	(0.110)
Civic Participation	0.0426	0.0415		0.0423
	(0.129)	(0.129)		(0.129)
Personal Relations	-0.513***		-0.514***	-0.513***
	(0.121)		(0.121)	(0.121)
Trust and Cooperative	-0.0321	-0.0320	-0.0324	
	(0.134)	(0.134)	(0.134)	
Constant	14.51***	14.37***	14.37***	14.41***
	(0.766)	(0.763)	(0.764)	(0.764)
Number of observations	47169	47169	47169	47169
Number of individuals	6747	6747	6747	6747
R^2 within	0.0229	0.0231	0.0228	0.0226
R^2 overall	0.0872	0.0873	0.0871	0.0871
R^2 between	0.117	0.118	0.117	0.118

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Errors are clustered at the individual level. Baseline for time dummies: pre-pandemic period, measured for each individual at one point between 2017 and 2019. Baseline for social capital is 0, i.e. having low social capital.

Included controls: age, age squared, gender, marital status, income quintiles dummies (2-5), macro region dummies, household composition, Both employed and self-employed, self-employed or unemployed (base: employed), bachelor, diploma, A levels, no education (base: GSCE), has previously diagnosed health conditions, is at risk of getting Covid-19 according to NHS and the remaining three social capital components.

Table B.4: Life Satisfaction regressions on social capital

	(1) Friends	(2) Personal Relations	(3) Putnam Groups	(4) Trust and Cooperative
	Can rely on and open up to friends	Belonging to and talking to neighbours	Active member of Putnam's groups	Can trust and get help from neighbours
May20	-0.339***	-0.359***	-0.369***	-0.385***
	(0.0323)	(0.0272)	(0.0273)	(0.0261)
July20	-0.248***	-0.197***	-0.243***	-0.250***
	(0.0343)	(0.0294)	(0.0291)	(0.0282)
September20	-0.312***	-0.298***	-0.342***	-0.345***
	(0.0336)	(0.0292)	(0.0289)	(0.0276)
November20	-0.279***	-0.313***	-0.320***	-0.353***
	(0.0343)	(0.0298)	(0.0298)	(0.0285)
January21	-0.483***	-0.522***	-0.555***	-0.557***
	(0.0378)	(0.0329)	(0.0332)	(0.0325)
March21	-0.357***	-0.348***	-0.394***	-0.395***
	(0.0357)	(0.0305)	(0.0307)	(0.0293)
Sep21	-0.323***	-0.271***	-0.328***	-0.335***
	(0.0372)	(0.0316)	(0.0314)	(0.0301)
SC=1	0.226***	0.340***	0.166***	0.0861**
	(0.0338)	(0.0374)	(0.0379)	(0.0424)
May20 × SC=1	-0.137***	-0.151***	-0.145***	-0.0915
	(0.0456)	(0.0524)	(0.0532)	(0.0596)
July20 × SC=1	-0.0210	-0.211***	-0.0597	-0.0418
	(0.0485)	(0.0545)	(0.0563)	(0.0603)
September20 × SC=1	-0.137***	-0.271***	-0.147***	-0.156**
	(0.0474)	(0.0529)	(0.0548)	(0.0614)
November20 × SC=1	-0.157***	-0.135**	-0.137**	-0.000959
	(0.0493)	(0.0557)	(0.0561)	(0.0635)
January21 × SC=1	-0.206***	-0.202***	-0.105*	-0.115*
	(0.0491)	(0.0561)	(0.0569)	(0.0616)
March21 × SC=1	-0.117**	-0.223***	-0.0761	-0.0885
	(0.0502)	(0.0569)	(0.0567)	(0.0632)
Sep21 × SC=1	-0.0488	-0.263***	-0.0777	-0.0585
	(0.0519)	(0.0588)	(0.0600)	(0.0664)
Controls				
Female	-0.00863	-0.00886	-0.00908	-0.00905
	(0.0270)	(0.0270)	(0.0270)	(0.0270)

Age	-0.0196***	-0.0210***	-0.0202***	-0.0199***
	(0.00609)	(0.00609)	(0.00609)	(0.00610)
age2	0.000260***	0.000273***	0.000265***	0.000263***
	(0.0000564)	(0.0000564)	(0.0000564)	(0.0000564)
Living with a partner	0.128***	0.119***	0.122***	0.126***
	(0.0409)	(0.0409)	(0.0409)	(0.0409)
London	-0.588**	-0.578**	-0.588**	-0.579**
	(0.245)	(0.243)	(0.242)	(0.244)
Wales	0.00810	0.00895	0.00891	0.00760
	(0.0601)	(0.0602)	(0.0602)	(0.0601)
Scotland	-0.00672	-0.00651	-0.00762	-0.00701
	(0.0453)	(0.0453)	(0.0453)	(0.0453)
NorthIre	0.0317	0.0320	0.0341	0.0327
	(0.0803)	(0.0802)	(0.0802)	(0.0803)
Household size	-0.0182	-0.0173	-0.0180	-0.0181
	(0.0197)	(0.0198)	(0.0197)	(0.0197)
quintile 2	0.00847	0.00582	0.00733	0.00691
	(0.0293)	(0.0293)	(0.0293)	(0.0293)
quintile 3	0.0202	0.0180	0.0204	0.0189
	(0.0307)	(0.0307)	(0.0307)	(0.0306)
quintile 4	0.00576	0.00250	0.00576	0.00402
	(0.0315)	(0.0315)	(0.0315)	(0.0315)
quintile 5	0.0341	0.0304	0.0340	0.0335
	(0.0346)	(0.0346)	(0.0346)	(0.0346)
self-employed	0.116**	0.115**	0.116**	0.117**
	(0.0497)	(0.0500)	(0.0498)	(0.0499)
unemployed	0.0625*	0.0606*	0.0621*	0.0619*
	(0.0335)	(0.0338)	(0.0337)	(0.0336)
both	0.0447	0.0415	0.0484	0.0477
	(0.0923)	(0.0921)	(0.0921)	(0.0922)
BA or higher	0.111***	0.110***	0.111***	0.110***
	(0.0349)	(0.0349)	(0.0349)	(0.0349)
Diploma or equivalent	-0.0250	-0.0254	-0.0249	-0.0256
	(0.0451)	(0.0451)	(0.0452)	(0.0452)
A Level or equivalent	0.0703	0.0683	0.0692	0.0688
	(0.0493)	(0.0494)	(0.0494)	(0.0494)
No education	-0.0516	-0.0527	-0.0511	-0.0515
	(0.0412)	(0.0412)	(0.0412)	(0.0412)
Has health condition	-0.168***	-0.169***	-0.169***	-0.169***
	(0.0265)	(0.0265)	(0.0265)	(0.0265)
NHS shielded patient	-0.204***	-0.206***	-0.204***	-0.205***

	(0.0513)	(0.0514)	(0.0513)	(0.0513)
Irish	-0.248*	-0.246*	-0.247*	-0.247*
	(0.128)	(0.128)	(0.128)	(0.128)
Other White	-0.157*	-0.155*	-0.156*	-0.156*
	(0.0810)	(0.0810)	(0.0810)	(0.0810)
Mixed	-0.381***	-0.381***	-0.382***	-0.382***
	(0.129)	(0.129)	(0.129)	(0.129)
Black	-0.246**	-0.248**	-0.251**	-0.248**
	(0.120)	(0.120)	(0.120)	(0.120)
BIP	-0.132	-0.134	-0.134	-0.133
	(0.0881)	(0.0882)	(0.0880)	(0.0881)
Chinese or Asian	-0.0983	-0.0953	-0.0988	-0.0971
	(0.125)	(0.125)	(0.125)	(0.125)
Arab	-0.231	-0.231	-0.232	-0.229
	(0.239)	(0.240)	(0.239)	(0.239)
mean couple	0.215***	0.223***	0.220***	0.216***
	(0.0562)	(0.0563)	(0.0562)	(0.0562)
mean London	0.430*	0.420*	0.429*	0.421*
	(0.249)	(0.248)	(0.246)	(0.249)
mean hhcomposition	-0.00370	-0.00421	-0.00355	-0.00381
	(0.0242)	(0.0242)	(0.0242)	(0.0242)
mean quintile 2	0.199***	0.201***	0.200***	0.200***
	(0.0724)	(0.0723)	(0.0723)	(0.0723)
mean quintile 3	0.242***	0.244***	0.242***	0.243***
	(0.0704)	(0.0704)	(0.0704)	(0.0704)
mean quintile 4	0.483***	0.486***	0.483***	0.485***
	(0.0705)	(0.0705)	(0.0705)	(0.0706)
mean quintile 5	0.436***	0.440***	0.436***	0.437***
	(0.0705)	(0.0705)	(0.0705)	(0.0705)
mean both	-0.120	-0.117	-0.127	-0.124
	(0.140)	(0.139)	(0.139)	(0.139)
mean selfemployed	-0.161**	-0.161**	-0.163**	-0.163**
	(0.0769)	(0.0771)	(0.0770)	(0.0770)
mean unemployed	-0.0826	-0.0834	-0.0834	-0.0826
	(0.0555)	(0.0556)	(0.0555)	(0.0555)
Social Network support		0.134***	0.135***	0.135***
		(0.0261)	(0.0261)	(0.0261)
Civic Participation	0.0810***	0.0809***		0.0812***
	(0.0301)	(0.0301)		(0.0301)
Personal Relations	0.178***		0.179***	0.178***
	(0.0287)		(0.0287)	(0.0287)

Trust and Cooperative	0.0228	0.0229	0.0228	
	(0.0320)	(0.0320)	(0.0320)	
Constant	5.005***	5.035***	5.042***	5.044***
	(0.174)	(0.174)	(0.174)	(0.174)
Number of observations	36671	36671	36671	36671
Number of individuals	6557	6557	6557	6557
R^2 within	0.0205	0.0207	0.0199	0.0199
R^2 overall	0.0609	0.0611	0.0606	0.0605
R^2 between	0.106	0.107	0.106	0.106

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Errors are clustered at the individual level.
Baseline for time dummies: pre-pandemic period, measured for each individual at one point between 2017 and 2019. Baseline for social capital is 0, i.e. having low social capital.
Included controls: age, age squared, gender, marital status, income quintiles dummies (2-5), macro region dummies, household composition, Both employed and self-employed, self-employed or unemployed (base: employed), bachelor, diploma, A levels, no education (base: GSCE), has previously diagnosed health conditions, is at risk of getting Covid-19 according to NHS and the remaining three social capital components.

Table B.5: Life satisfaction regression on Social capital with GHQ control

	(1) Friends	(2) Personal Relations	(3) Putnam Groups	(4) Trust and Cooperative
May20	-0.225***	-0.244***	-0.246***	-0.261***
	(0.0310)	(0.0259)	(0.0260)	(0.0249)
July20	-0.177***	-0.132***	-0.168***	-0.177***
	(0.0329)	(0.0282)	(0.0280)	(0.0272)
September20	-0.219***	-0.210***	-0.245***	-0.248***
	(0.0321)	(0.0278)	(0.0275)	(0.0263)
November20	-0.119***	-0.153***	-0.152***	-0.174***
	(0.0332)	(0.0288)	(0.0289)	(0.0276)
January21	-0.305***	-0.346***	-0.362***	-0.370***
	(0.0361)	(0.0313)	(0.0315)	(0.0309)
March21	-0.223***	-0.216***	-0.251***	-0.251***
	(0.0344)	(0.0294)	(0.0296)	(0.0283)
Sep21	-0.228***	-0.182***	-0.235***	-0.238***
	(0.0364)	(0.0309)	(0.0309)	(0.0294)
SC=1	0.153***	0.245***	0.144***	0.0556
	(0.0300)	(0.0335)	(0.0337)	(0.0381)
May20 × SC=1	-0.102**	-0.103**	-0.114**	-0.0596
	(0.0432)	(0.0500)	(0.0506)	(0.0564)
July20 × SC=1	-0.00545	-0.166***	-0.0470	-0.0167
	(0.0466)	(0.0527)	(0.0540)	(0.0578)
September20 × SC=1	-0.106**	-0.204***	-0.103**	-0.105*
	(0.0451)	(0.0505)	(0.0523)	(0.0583)
November20 × SC=1	-0.113**	-0.0666	-0.0827	0.00970
	(0.0477)	(0.0541)	(0.0540)	(0.0616)
January21 × SC=1	-0.168***	-0.133**	-0.0927*	-0.0705
	(0.0462)	(0.0528)	(0.0534)	(0.0580)
March21 × SC=1	-0.0842*	-0.163***	-0.0495	-0.0628
	(0.0484)	(0.0550)	(0.0548)	(0.0611)
Sep21 × SC=1	-0.0405	-0.228***	-0.0521	-0.0471
	(0.0508)	(0.0578)	(0.0588)	(0.0656)
GHQ	-0.0998***	-0.0998***	-0.0999***	-0.0999***
	(0.00170)	(0.00170)	(0.00170)	(0.00170)
Female	0.131***	0.131***	0.131***	0.131***
	(0.0228)	(0.0228)	(0.0228)	(0.0228)
Age	-0.0273***	-0.0281***	-0.0276***	-0.0275***

	(0.00515)	(0.00515)	(0.00515)	(0.00515)
age2	0.000254***	0.000262***	0.000257***	0.000256***
	(0.0000477)	(0.0000477)	(0.0000477)	(0.0000477)
Living with a partner	0.110***	0.104***	0.106***	0.109***
	(0.0389)	(0.0390)	(0.0390)	(0.0390)
London	-0.387	-0.379	-0.385	-0.379
	(0.239)	(0.237)	(0.237)	(0.238)
Wales	0.0160	0.0165	0.0165	0.0157
	(0.0517)	(0.0517)	(0.0517)	(0.0517)
Scotland	-0.0221	-0.0219	-0.0226	-0.0223
	(0.0377)	(0.0377)	(0.0377)	(0.0377)
NorthIre	0.0536	0.0539	0.0551	0.0542
	(0.0673)	(0.0672)	(0.0673)	(0.0673)
Household size	-0.0210	-0.0202	-0.0207	-0.0210
	(0.0188)	(0.0189)	(0.0188)	(0.0188)
quintile 2	-0.00178	-0.00407	-0.00289	-0.00324
	(0.0282)	(0.0282)	(0.0282)	(0.0282)
quintile 3	0.00758	0.00569	0.00725	0.00645
	(0.0295)	(0.0295)	(0.0296)	(0.0295)
quintile 4	-0.000498	-0.00323	-0.000761	-0.00212
	(0.0306)	(0.0306)	(0.0306)	(0.0306)
quintile 5	0.0144	0.0113	0.0142	0.0137
	(0.0336)	(0.0336)	(0.0336)	(0.0336)
selfemployed	0.115**	0.116**	0.115**	0.116**
	(0.0484)	(0.0487)	(0.0486)	(0.0486)
unemployed	0.0693**	0.0691**	0.0681**	0.0692**
	(0.0324)	(0.0328)	(0.0326)	(0.0325)
both	0.0843	0.0819	0.0864	0.0870
	(0.0882)	(0.0880)	(0.0880)	(0.0880)
BA or higher	0.135***	0.135***	0.135***	0.135***
	(0.0292)	(0.0292)	(0.0292)	(0.0292)
Diploma or equivalent	0.0163	0.0161	0.0164	0.0160
	(0.0378)	(0.0378)	(0.0378)	(0.0378)
A Level or equivalent	0.0685*	0.0673	0.0678	0.0676
	(0.0416)	(0.0416)	(0.0416)	(0.0416)
none	-0.0614*	-0.0619*	-0.0610*	-0.0613*
	(0.0355)	(0.0355)	(0.0355)	(0.0355)
Has health condition	-0.0766***	-0.0769***	-0.0770***	-0.0770***
	(0.0225)	(0.0225)	(0.0225)	(0.0225)
NHS shielded patient	-0.107**	-0.108**	-0.107**	-0.107**
	(0.0423)	(0.0424)	(0.0423)	(0.0423)

Irish	-0.140	-0.139	-0.140	-0.139
	(0.106)	(0.106)	(0.106)	(0.106)
Other White	-0.156**	-0.155**	-0.156**	-0.156**
	(0.0680)	(0.0681)	(0.0681)	(0.0681)
Mixed	-0.253**	-0.252**	-0.253**	-0.253**
	(0.116)	(0.116)	(0.116)	(0.116)
Black	-0.263***	-0.264***	-0.266***	-0.264***
	(0.0959)	(0.0959)	(0.0958)	(0.0958)
BIP	-0.134**	-0.135**	-0.136**	-0.134**
	(0.0671)	(0.0672)	(0.0670)	(0.0671)
Chinese/Asian Background	-0.114	-0.112	-0.114	-0.113
	(0.101)	(0.101)	(0.101)	(0.101)
Arab	-0.0865	-0.0887	-0.0874	-0.0851
	(0.282)	(0.281)	(0.282)	(0.282)
mean couple	0.145***	0.151***	0.148***	0.145***
	(0.0501)	(0.0501)	(0.0501)	(0.0501)
mean London	0.255	0.248	0.253	0.247
	(0.243)	(0.241)	(0.241)	(0.242)
mean hhcomposition	0.00394	0.00351	0.00400	0.00397
	(0.0223)	(0.0223)	(0.0223)	(0.0223)
mean quintile 2	0.118*	0.120**	0.118**	0.119**
	(0.0604)	(0.0604)	(0.0603)	(0.0604)
mean quintile 3	0.150**	0.152**	0.150**	0.151**
	(0.0598)	(0.0598)	(0.0598)	(0.0598)
mean quintile 4	0.347***	0.350***	0.347***	0.349***
	(0.0599)	(0.0599)	(0.0599)	(0.0599)
mean quintile 5	0.289***	0.291***	0.289***	0.289***
	(0.0613)	(0.0613)	(0.0613)	(0.0613)
mean both	-0.175	-0.173	-0.179	-0.178
	(0.131)	(0.131)	(0.131)	(0.131)
mean selfemployed	-0.138**	-0.138**	-0.138**	-0.139**
	(0.0689)	(0.0692)	(0.0691)	(0.0691)
mean unemployed	-0.0342	-0.0356	-0.0335	-0.0344
	(0.0480)	(0.0482)	(0.0481)	(0.0480)
Civic Participation	0.0813***	0.0811***		0.0814***
	(0.0255)	(0.0255)		(0.0255)
Social Network support		0.0836***	0.0836***	0.0836***
		(0.0220)	(0.0220)	(0.0220)
Personal Relations	0.124***		0.125***	0.125***
	(0.0246)		(0.0246)	(0.0246)
Trust and Cooperative	0.0149	0.0149	0.0148	

	(0.0273)	(0.0273)	(0.0273)	
Constant	6.549***	6.567***	6.576***	6.579***
	(0.149)	(0.148)	(0.149)	(0.149)
Number of observations	36671	36671	36671	36671
Number of individuals	6557	6557	6557	6557
R^2 within	0.0672	0.0674	0.0668	0.0668
R^2 overall	0.213	0.214	0.213	0.213
R^2 between	0.372	0.372	0.372	0.372

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Errors are clustered at the individual level. Baseline for time dummies: pre-pandemic period, measured for each individual at one point between 2017 and 2019. Baseline for social capital is 0, i.e. having low social capital.
Includes controls for mental health.

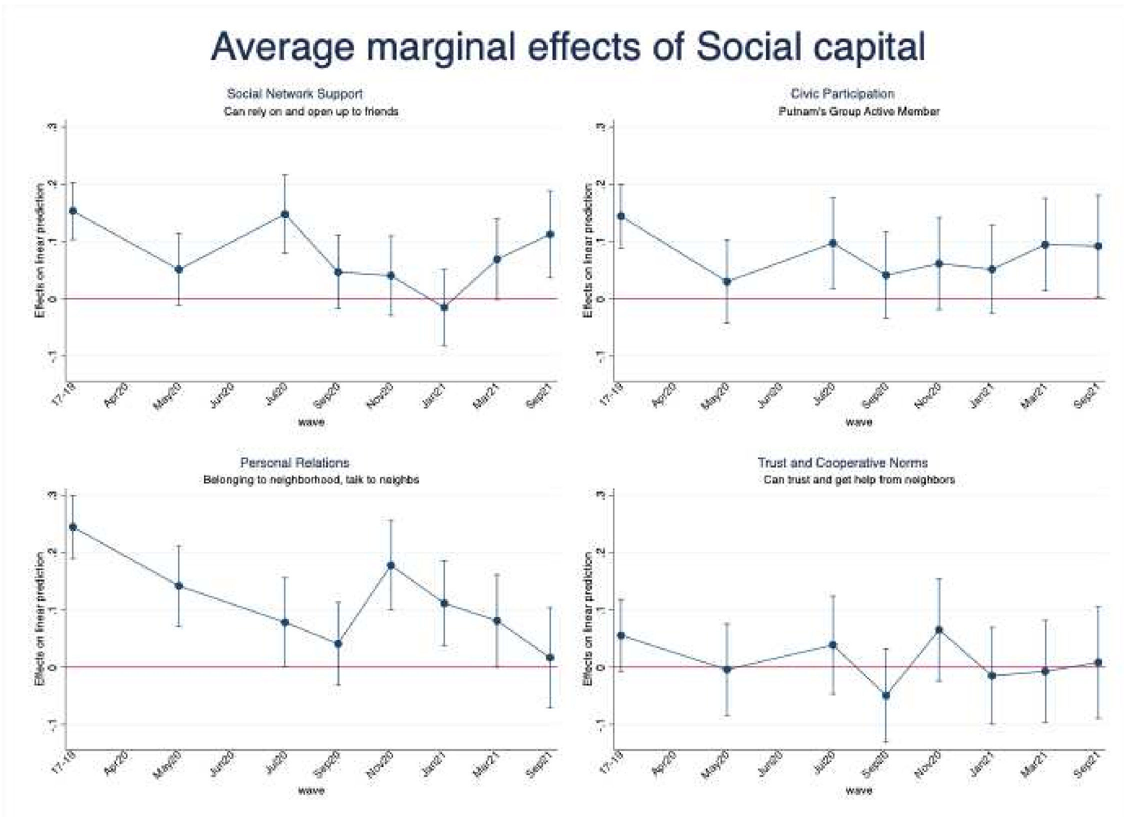


Figure B.1: AMEs of regression of life satisfaction with GHQ as control

Table B.6: Main results with inclusion of autoregressive GHQ measure

	(1) Friends	(2) Personal Relations	(3) Putnam Groups	(4) Trust and Cooperative
April20	1.130***	1.198***	1.315***	1.275***
	(0.109)	(0.0917)	(0.0906)	(0.0873)
May20	1.119***	1.113***	1.185***	1.198***
	(0.105)	(0.0888)	(0.0878)	(0.0846)
June20	1.260***	1.206***	1.251***	1.308***
	(0.105)	(0.0916)	(0.0888)	(0.0868)
July20	0.724***	0.615***	0.719***	0.708***
	(0.103)	(0.0895)	(0.0872)	(0.0850)
September20	0.934***	0.823***	0.925***	0.940***
	(0.105)	(0.0901)	(0.0895)	(0.0850)
November20	1.589***	1.562***	1.627***	1.749***
	(0.111)	(0.0956)	(0.0951)	(0.0909)
January21	1.762***	1.689***	1.847***	1.822***
	(0.125)	(0.109)	(0.109)	(0.105)
March21	1.331***	1.254***	1.369***	1.398***
	(0.113)	(0.0957)	(0.0952)	(0.0916)
Sep21	0.934***	0.815***	0.859***	0.929***
	(0.113)	(0.0977)	(0.0947)	(0.0914)
SC=1	-0.492***	-0.723***	-0.136	-0.101
	(0.118)	(0.119)	(0.122)	(0.144)
April20 × SC=1	0.514***	0.551***	0.166	0.488**
	(0.155)	(0.170)	(0.176)	(0.193)
May20 × SC=1	0.283*	0.480***	0.282*	0.281
	(0.150)	(0.163)	(0.168)	(0.184)
June20 × SC=1	0.225	0.525***	0.459***	0.247
	(0.153)	(0.163)	(0.175)	(0.185)
July20 × SC=1	0.115	0.474***	0.133	0.241
	(0.149)	(0.159)	(0.167)	(0.181)
September20 × SC=1	0.292*	0.667***	0.389**	0.455**
	(0.151)	(0.165)	(0.170)	(0.195)
November20 × SC=1	0.404**	0.691***	0.576***	0.0969
	(0.159)	(0.172)	(0.174)	(0.195)
January21 × SC=1	0.333**	0.687***	0.126	0.359*
	(0.160)	(0.175)	(0.176)	(0.203)
March21 × SC=1	0.275*	0.600***	0.249	0.215
	(0.161)	(0.176)	(0.178)	(0.197)

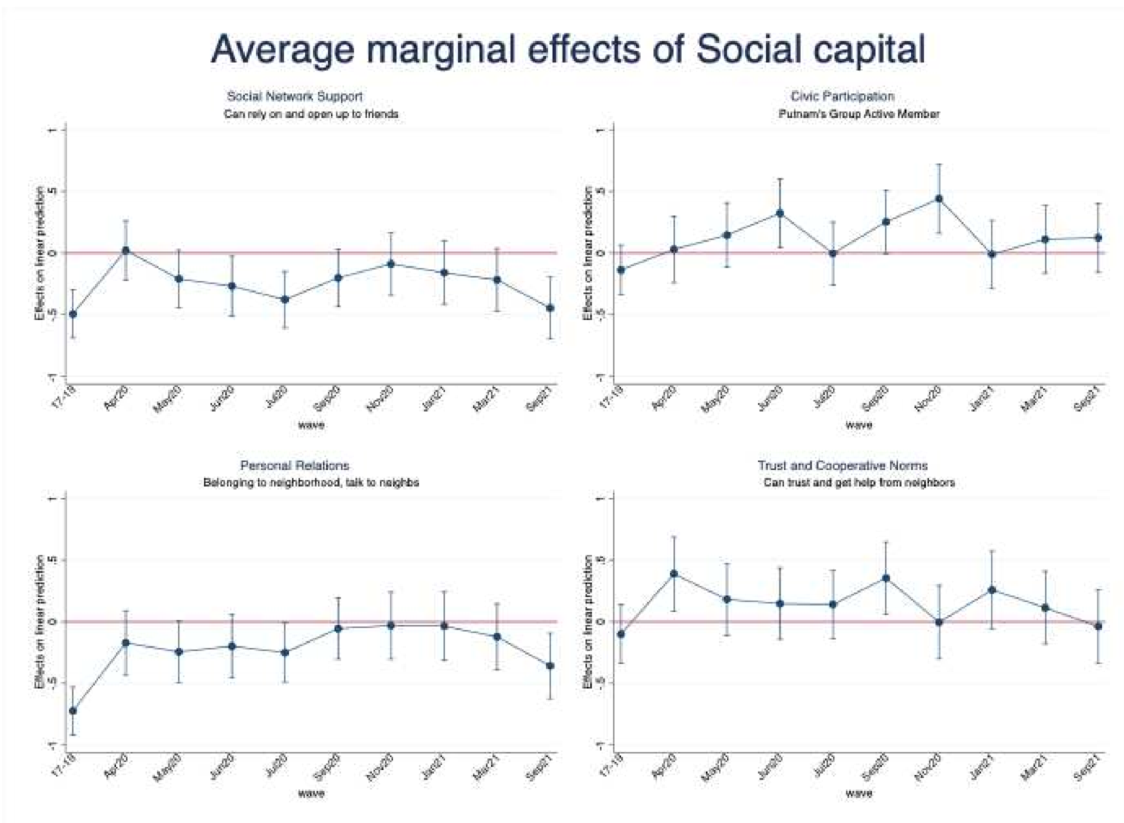
Sep21 × SC=1	0.0475	0.366**	0.260	0.0638
	(0.158)	(0.168)	(0.178)	(0.193)
Female	1.016***	1.035***	1.035***	1.023***
	(0.103)	(0.0957)	(0.0957)	(0.0994)
Age	-0.113***	-0.0771***	-0.0793***	-0.112***
	(0.0263)	(0.0227)	(0.0227)	(0.0242)
age2	0.000466**	0.000221	0.000242	0.000439**
	(0.000234)	(0.000205)	(0.000205)	(0.000219)
Living with a partner	-0.103	-0.0886	-0.0907	-0.0937
	(0.135)	(0.130)	(0.130)	(0.132)
London	2.035***	1.971***	2.007***	2.003***
	(0.599)	(0.532)	(0.527)	(0.526)
Wales	0.0316	0.173	0.175	0.165
	(0.240)	(0.221)	(0.221)	(0.219)
Scotland	0.0368	0.0657	0.0680	0.0263
	(0.180)	(0.169)	(0.169)	(0.180)
NorthIre	0.416	-0.264	-0.273	0.0696
	(0.301)	(0.286)	(0.286)	(0.293)
Household size	0.00386	-0.0155	-0.0141	-0.0216
	(0.0599)	(0.0579)	(0.0578)	(0.0577)
quintile 2	0.00430	0.0137	0.0104	0.0106
	(0.0759)	(0.0750)	(0.0750)	(0.0748)
quintile 3	-0.0539	-0.0643	-0.0723	-0.0717
	(0.0793)	(0.0771)	(0.0771)	(0.0770)
quintile 4	0.0355	0.0457	0.0381	0.0325
	(0.0855)	(0.0827)	(0.0829)	(0.0825)
quintile 5	-0.0475	-0.0388	-0.0470	-0.0435
	(0.0953)	(0.0928)	(0.0929)	(0.0926)
both	0.221	0.371	0.348	0.335
	(0.367)	(0.355)	(0.355)	(0.354)
selfemployed	-0.0645	-0.0751	-0.0868	-0.0819
	(0.166)	(0.161)	(0.161)	(0.160)
unemployed	0.0553	0.0622	0.0392	0.0362
	(0.107)	(0.104)	(0.104)	(0.103)
BA or higher	0.218	0.197	0.195	0.240*
	(0.134)	(0.125)	(0.125)	(0.130)
Diploma or equivalent	0.274	0.340**	0.338**	0.290*
	(0.171)	(0.158)	(0.158)	(0.169)
A Level or equivalent	0.112	0.137	0.135	0.0685
	(0.188)	(0.172)	(0.172)	(0.181)

none	-0.182	-0.223	-0.228	-0.139
	(0.154)	(0.144)	(0.144)	(0.148)
Has health condition	0.624***	0.506***	0.506***	0.607***
	(0.101)	(0.0953)	(0.0953)	(0.0986)
NHS shielded patient	0.598***	0.519***	0.518***	0.690***
	(0.193)	(0.171)	(0.171)	(0.188)
Irish	0.847	0.925*	0.930*	0.720
	(0.517)	(0.510)	(0.509)	(0.486)
Other White	0.0448	0.0847	0.0852	0.146
	(0.306)	(0.298)	(0.297)	(0.315)
Mixed	0.304	0.309	0.308	0.523
	(0.502)	(0.468)	(0.468)	(0.503)
Black	-0.133	-0.530	-0.520	-0.446
	(0.449)	(0.417)	(0.417)	(0.433)
BIP	0.0842	0.157	0.159	-0.173
	(0.358)	(0.297)	(0.297)	(0.345)
Chinese/Asian Background	-0.105	-0.476	-0.469	-0.00343
	(0.475)	(0.467)	(0.467)	(0.465)
Arab	1.486	0.511	0.521	0.0784
	(1.552)	(1.554)	(1.550)	(1.474)
mean couple	-0.646***	-0.571***	-0.566***	-0.571***
	(0.203)	(0.190)	(0.190)	(0.196)
mean London	-1.710***	-1.724***	-1.757***	-1.720***
	(0.622)	(0.550)	(0.545)	(0.554)
mean hhcomposition	0.0262	0.0537	0.0518	0.0564
	(0.0825)	(0.0803)	(0.0802)	(0.0806)
mean quintile 2	-0.502*	-0.263	-0.261	-0.550**
	(0.259)	(0.239)	(0.239)	(0.249)
mean quintile 3	-0.401	-0.172	-0.165	-0.379
	(0.254)	(0.233)	(0.233)	(0.245)
mean quintile 4	-0.867***	-0.567**	-0.557**	-0.883***
	(0.257)	(0.238)	(0.238)	(0.252)
mean quintile 5	-0.908***	-0.780***	-0.769***	-1.015***
	(0.250)	(0.236)	(0.236)	(0.241)
mean both	-0.465	-0.750	-0.719	-0.837*
	(0.513)	(0.521)	(0.521)	(0.480)
mean selfemployed	0.500*	0.501*	0.516**	0.492*
	(0.278)	(0.262)	(0.261)	(0.260)
mean unemployed	0.184	0.197	0.216	0.331*
	(0.203)	(0.190)	(0.190)	(0.198)
Civic Participation p	0.0317	0.0970		0.0148

	(0.117)	(0.109)		(0.115)
Personal Relations	-0.226**		-0.267**	-0.277**
	(0.113)		(0.106)	(0.109)
Trust and Cooperative	0.0576	0.0373	0.0369	
	(0.126)	(0.118)	(0.118)	
Social Networks Support		-0.178*	-0.180*	-0.124
		(0.0944)	(0.0944)	(0.0988)
Lag GHQ	0.378***	0.462***	0.462***	0.386***
	(0.0134)	(0.0131)	(0.0131)	(0.0127)
Constant	11.55***	9.215***	9.194***	11.23***
	(0.796)	(0.683)	(0.683)	(0.718)
Number of observations	44649	46726	46726	47168
Number of individuals	6350	6676	6676	6746
R^2 within	0.0229	0.0235	0.0232	0.0226
R^2 overall	0.206	0.248	0.248	0.207
R^2 between	0.287	0.354	0.353	0.291

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Errors are clustered at the individual level.
Baseline for time dummies: pre-pandemic period, measured for each individual at one point between 2017 and 2019. Baseline for social capital is 0, i.e. having low social capital.
The lagged GHQ measure is with respect to the collection of the social capital variable. Lagged in this case means it was collected in the wave prior to the collection of the social capital measure.

Figure B.2: AMEs of regression with lagged GHQ as control to correct for endogeneity



B.4 Additional Robustness checks

Table B.7: FE regression

	GHQ				Life satisfaction			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
April20	1.280***	1.365***	1.489***	1.441***				
	(0.164)	(0.155)	(0.153)	(0.152)				
May20	1.267***	1.269***	1.353***	1.371***	-0.306***	-0.337***	-0.349***	-0.360***
	(0.166)	(0.159)	(0.155)	(0.154)	(0.0549)	(0.0519)	(0.0516)	(0.0515)
June20	1.372***	1.371***	1.429***	1.487***				
	(0.168)	(0.164)	(0.159)	(0.159)				
July20	0.878***	0.806***	0.924***	0.912***	-0.222***	-0.182***	-0.229***	-0.231***
	(0.172)	(0.167)	(0.163)	(0.162)	(0.0582)	(0.0554)	(0.0552)	(0.0548)
September20	1.091***	1.028***	1.149***	1.144***	-0.281***	-0.277***	-0.325***	-0.320***
	(0.181)	(0.175)	(0.172)	(0.171)	(0.0609)	(0.0588)	(0.0585)	(0.0578)
November20	1.771***	1.761***	1.845***	1.962***	-0.239***	-0.291***	-0.297***	-0.324***
	(0.190)	(0.185)	(0.182)	(0.180)	(0.0642)	(0.0613)	(0.0611)	(0.0606)
January21	1.965***	1.917***	2.091***	2.055***	-0.465***	-0.515***	-0.550***	-0.548***
	(0.203)	(0.197)	(0.196)	(0.193)	(0.0683)	(0.0653)	(0.0653)	(0.0649)
March21	1.546***	1.497***	1.623***	1.637***	-0.319***	-0.322***	-0.370***	-0.366***
	(0.206)	(0.200)	(0.199)	(0.197)	(0.0690)	(0.0664)	(0.0657)	(0.0655)
Sep21	1.186***	1.096***	1.162***	1.213***	-0.275***	-0.236***	-0.297***	-0.297***
	(0.229)	(0.224)	(0.222)	(0.221)	(0.0780)	(0.0754)	(0.0751)	(0.0741)
SC=1	0				0			
	(.)				(.)			
April20 × SC=1	0.533***	0.537***	0.181	0.443**				
	(0.153)	(0.173)	(0.179)	(0.196)				
May20 × SC=1	0.326**	0.489***	0.310*	0.247	-0.144***	-0.119**	-0.115**	-0.0713
	(0.147)	(0.164)	(0.169)	(0.185)	(0.0465)	(0.0539)	(0.0545)	(0.0609)
June20 × SC=1	0.348**	0.532***	0.478***	0.238				
	(0.150)	(0.165)	(0.175)	(0.187)				
July20 × SC=1	0.161	0.480***	0.153	0.212	-0.0245	-0.170***	-0.0252	-0.0133
	(0.147)	(0.161)	(0.170)	(0.183)	(0.0494)	(0.0559)	(0.0576)	(0.0616)
September20 × SC=1	0.298**	0.664***	0.377**	0.432**	-0.143***	-0.233***	-0.104*	-0.136**
	(0.150)	(0.168)	(0.172)	(0.198)	(0.0484)	(0.0544)	(0.0561)	(0.0629)
November20 × SC=1	0.439***	0.705***	0.588***	0.0758	-0.169***	-0.0878	-0.100*	0.0269
	(0.157)	(0.174)	(0.175)	(0.197)	(0.0503)	(0.0575)	(0.0570)	(0.0648)
January21 × SC=1	0.331**	0.691***	0.143	0.338*	-0.213***	-0.162***	-0.0715	-0.0884
	(0.158)	(0.177)	(0.178)	(0.205)	(0.0501)	(0.0578)	(0.0582)	(0.0629)
March21 × SC=1	0.278*	0.583***	0.262	0.196	-0.123**	-0.179***	-0.0424	-0.0576
	(0.158)	(0.178)	(0.180)	(0.199)	(0.0510)	(0.0580)	(0.0576)	(0.0642)
Sep21 × SC=1	0.0717	0.387**	0.292	0.0380	-0.0548	-0.217***	-0.0333	-0.0235
	(0.156)	(0.172)	(0.180)	(0.195)	(0.0528)	(0.0603)	(0.0612)	(0.0677)
Constant	16.17***	14.89***	15.85***	16.01***	0.501	0.917	0.539	0.542
	(3.946)	(3.970)	(3.953)	(3.948)	(1.193)	(1.200)	(1.196)	(1.193)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	47169	47169	47169	47169	36671	36671	36671	36671
Number of individuals	6747	6747	6747	6747	6557	6557	6557	6557
R^2	0.0231	0.0233	0.0230	0.0229	0.0235	0.0233	0.0227	0.0228

Notes: columns are estimated on each social capital component: (1) corresponds to Social Network support, (2) Personal Relations, (3) Civic Participation, (4) Trust and cooperative norms
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Errors are clustered at the individual level.
Model is estimated using Fixed effects. Baseline for time dummies: pre-pandemic period, measured for each individual at one point between 2017 and 2019.
Socio-demographic controls are included

B.5 Hausman Taylor

Table B.8: Hausman Taylor

	GHQ				Life Satisfaction			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
April20	1.150***	1.254***	1.363***	1.315***				0
	(0.107)	(0.0920)	(0.0907)	(0.0877)				(.)
May20	1.127***	1.147***	1.212***	1.232***	-0.317***	-0.344***	-0.352***	-0.367***
	(0.102)	(0.0880)	(0.0868)	(0.0838)	(0.0323)	(0.0269)	(0.0270)	(0.0258)
June20	1.228***	1.243***	1.284***	1.345***				0
	(0.102)	(0.0905)	(0.0876)	(0.0858)				(.)
July20	0.720***	0.665***	0.765***	0.756***	-0.229***	-0.185***	-0.229***	-0.235***
	(0.101)	(0.0887)	(0.0861)	(0.0839)	(0.0342)	(0.0291)	(0.0289)	(0.0279)
September20	0.923***	0.879***	0.978***	0.979***	-0.291***	-0.282***	-0.326***	-0.327***
	(0.103)	(0.0891)	(0.0882)	(0.0839)	(0.0335)	(0.0290)	(0.0286)	(0.0272)
November20	1.593***	1.602***	1.668***	1.786***	-0.253***	-0.298***	-0.302***	-0.333***
	(0.108)	(0.0937)	(0.0934)	(0.0894)	(0.0340)	(0.0294)	(0.0295)	(0.0280)
January21	1.831***	1.806***	1.959***	1.925***	-0.481***	-0.528***	-0.558***	-0.560***
	(0.121)	(0.108)	(0.109)	(0.104)	(0.0374)	(0.0323)	(0.0325)	(0.0318)
March21	1.346***	1.322***	1.427***	1.443***	-0.336***	-0.334***	-0.378***	-0.377***
	(0.110)	(0.0944)	(0.0939)	(0.0904)	(0.0355)	(0.0300)	(0.0302)	(0.0287)
May21	0.949***	0.887***	0.924***	0.980***	-0.297***	-0.252***	-0.307***	-0.313***
	(0.109)	(0.0956)	(0.0926)	(0.0897)	(0.0368)	(0.0309)	(0.0308)	(0.0294)
Apr×SC=1	0.539***	0.513***	0.151	0.439**				
	(0.153)	(0.172)	(0.178)	(0.196)				
May×SC=1	0.323**	0.458***	0.281*	0.240	-0.141***	-0.138**	-0.134**	-0.0837
	(0.147)	(0.164)	(0.169)	(0.185)	(0.0466)	(0.0537)	(0.0543)	(0.0609)
Jun×SC=1	0.341**	0.502***	0.444**	0.221				
	(0.150)	(0.164)	(0.175)	(0.187)				
Jul×SC=1	0.157	0.450***	0.120	0.201	-0.0252	-0.195***	-0.0478	-0.0306
	(0.147)	(0.161)	(0.170)	(0.183)	(0.0494)	(0.0557)	(0.0573)	(0.0615)
Sep×SC=1	0.296**	0.637***	0.359**	0.420**	-0.141***	-0.257***	-0.132**	-0.148**
	(0.150)	(0.167)	(0.172)	(0.197)	(0.0485)	(0.0542)	(0.0560)	(0.0629)
Nov×SC=1	0.436***	0.677***	0.546***	0.0657	-0.166***	-0.118**	-0.124**	0.00749
	(0.157)	(0.173)	(0.175)	(0.197)	(0.0502)	(0.0570)	(0.0569)	(0.0648)
Jan×SC=1	0.338**	0.668***	0.123	0.341*	-0.214***	-0.191***	-0.0994*	-0.110*
	(0.158)	(0.176)	(0.178)	(0.205)	(0.0501)	(0.0574)	(0.0580)	(0.0628)
Mar×SC=1	0.284*	0.548***	0.224	0.189	-0.122**	-0.206***	-0.0654	-0.0814
	(0.158)	(0.177)	(0.179)	(0.199)	(0.0511)	(0.0579)	(0.0576)	(0.0645)
Sep21×SC=1	0.0743	0.340**	0.253	0.0282	-0.0546	-0.247***	-0.0655	-0.0485
	(0.156)	(0.170)	(0.179)	(0.195)	(0.0527)	(0.0599)	(0.0608)	(0.0676)
Social Network Support	-0.755***	-0.502***	-0.502***	-0.503***	0.237***	0.142***	0.142***	0.142***
	(0.132)	(0.112)	(0.112)	(0.112)	(0.0372)	(0.0268)	(0.0268)	(0.0268)
Personal relations	-0.486***	-0.919***	-0.486***	-0.491***	0.175***	0.326***	0.175***	0.175***

	(0.123)	(0.144)	(0.123)	(0.123)	(0.0292)	(0.0411)	(0.0292)	(0.0292)
Civic Participation	0.0177	0.0205	-0.180	0.0182	0.0922***	0.0912***	0.166***	0.0920***
	(0.132)	(0.132)	(0.150)	(0.132)	(0.0307)	(0.0307)	(0.0416)	(0.0307)
Trust Cooperative	-0.0777	-0.0803	-0.0774	-0.259	0.0349	0.0356	0.0349	0.0892*
	(0.137)	(0.137)	(0.137)	(0.165)	(0.0326)	(0.0326)	(0.0326)	(0.0463)
Controls								
age	-0.0884***	-0.0776**	-0.0829***	-0.0856***	0.0134*	0.00996	0.0122	0.0128*
	(0.0320)	(0.0321)	(0.0321)	(0.0321)	(0.00762)	(0.00762)	(0.00761)	(0.00762)
age2	0.0000983	-0.000000827	0.0000497	0.0000726	-0.0000418	-0.0000105	-0.0000306	-0.0000364
	(0.000285)	(0.000286)	(0.000286)	(0.000286)	(0.0000677)	(0.0000677)	(0.0000676)	(0.0000677)
Couple	-0.342***	-0.334***	-0.333***	-0.341***	0.221***	0.218***	0.219***	0.220***
	(0.114)	(0.114)	(0.114)	(0.114)	(0.0308)	(0.0307)	(0.0308)	(0.0308)
London	0.625***	0.623***	0.630***	0.629***	-0.200***	-0.198***	-0.200***	-0.200***
	(0.204)	(0.203)	(0.203)	(0.203)	(0.0523)	(0.0521)	(0.0521)	(0.0522)
Wales	0.145	0.142	0.145	0.144	0.0188	0.0173	0.0176	0.0172
	(0.256)	(0.255)	(0.256)	(0.256)	(0.0606)	(0.0606)	(0.0606)	(0.0606)
Scotland	-0.0322	-0.0293	-0.0285	-0.0324	-0.0178	-0.0185	-0.0190	-0.0182
	(0.226)	(0.226)	(0.226)	(0.226)	(0.0476)	(0.0475)	(0.0475)	(0.0475)
NorthIre	0.299	0.299	0.274	0.289	-0.00329	-0.00229	0.00146	-0.00156
	(0.338)	(0.338)	(0.339)	(0.339)	(0.0836)	(0.0835)	(0.0835)	(0.0836)
Household size	-0.0595	-0.0601	-0.0593	-0.0594	0.00879	0.00918	0.00905	0.00885
	(0.0467)	(0.0467)	(0.0466)	(0.0466)	(0.0128)	(0.0128)	(0.0128)	(0.0128)
quintile 2	-0.0140	-0.00902	-0.0114	-0.00867	0.0185	0.0159	0.0173	0.0170
	(0.0735)	(0.0733)	(0.0733)	(0.0735)	(0.0274)	(0.0274)	(0.0274)	(0.0274)
quintile 3	-0.123	-0.118	-0.125*	-0.117	0.0571**	0.0556*	0.0574**	0.0560**
	(0.0755)	(0.0754)	(0.0754)	(0.0755)	(0.0284)	(0.0284)	(0.0284)	(0.0283)
quintile 4	-0.0634	-0.0574	-0.0631	-0.0581	0.0819***	0.0801***	0.0823***	0.0806***
	(0.0804)	(0.0803)	(0.0804)	(0.0804)	(0.0291)	(0.0291)	(0.0292)	(0.0292)
quintile 5	-0.169*	-0.163*	-0.170*	-0.166*	0.113***	0.111***	0.114***	0.113***
	(0.0888)	(0.0886)	(0.0888)	(0.0888)	(0.0313)	(0.0312)	(0.0313)	(0.0313)
Both	0.309	0.312	0.294	0.301	-0.00954	-0.0118	-0.00736	-0.00725
	(0.321)	(0.320)	(0.321)	(0.320)	(0.0768)	(0.0766)	(0.0767)	(0.0768)
self-employed	0.0218	0.0296	0.0200	0.0218	0.0473	0.0467	0.0471	0.0478
	(0.137)	(0.137)	(0.137)	(0.137)	(0.0377)	(0.0378)	(0.0377)	(0.0378)
unemployed	0.154*	0.171*	0.150	0.158*	0.0246	0.0217	0.0237	0.0240
	(0.0916)	(0.0922)	(0.0921)	(0.0919)	(0.0275)	(0.0277)	(0.0276)	(0.0275)
NHS shielded patient	0.760***	0.755***	0.757***	0.758***	-0.167***	-0.169***	-0.168***	-0.167***
	(0.210)	(0.209)	(0.210)	(0.209)	(0.0519)	(0.0520)	(0.0520)	(0.0519)
Other White	-0.00779	-0.0204	-0.0121	-0.0141	-0.161*	-0.159*	-0.161*	-0.161*
	(0.346)	(0.347)	(0.346)	(0.347)	(0.0838)	(0.0839)	(0.0839)	(0.0838)

Chinese/Asian	-0.214	-0.213	-0.220	-0.208	-0.105	-0.103	-0.104	-0.104
	(0.495)	(0.495)	(0.494)	(0.495)	(0.127)	(0.127)	(0.127)	(0.127)
female	1.592***	1.596***	1.595***	1.596***	-0.0407	-0.0415	-0.0414	-0.0417
	(0.113)	(0.113)	(0.113)	(0.113)	(0.0276)	(0.0275)	(0.0275)	(0.0276)
BA or higher	-0.00741	-0.00619	-0.00728	-0.00682	0.181***	0.180***	0.181***	0.180***
	(0.146)	(0.146)	(0.146)	(0.146)	(0.0353)	(0.0352)	(0.0353)	(0.0352)
Diploma or equivalent	0.275	0.280	0.278	0.277	0.0139	0.0126	0.0138	0.0134
	(0.195)	(0.195)	(0.195)	(0.195)	(0.0459)	(0.0459)	(0.0459)	(0.0459)
A Level or equivalent	-0.117	-0.108	-0.111	-0.114	0.120**	0.117**	0.119**	0.119**
	(0.208)	(0.208)	(0.208)	(0.208)	(0.0505)	(0.0505)	(0.0505)	(0.0505)
No education	-0.0942	-0.0912	-0.0916	-0.0929	-0.0494	-0.0508	-0.0494	-0.0495
	(0.173)	(0.173)	(0.173)	(0.173)	(0.0421)	(0.0421)	(0.0421)	(0.0421)
Has health condition	1.025***	1.027***	1.027***	1.026***	-0.187***	-0.188***	-0.188***	-0.188***
	(0.113)	(0.113)	(0.113)	(0.113)	(0.0272)	(0.0272)	(0.0272)	(0.0272)
Irish	1.025*	1.020*	1.037*	1.031*	-0.256*	-0.253*	-0.257*	-0.255*
	(0.547)	(0.548)	(0.547)	(0.547)	(0.131)	(0.131)	(0.131)	(0.131)
Mixed	1.487**	1.497**	1.502**	1.490**	-0.426***	-0.429***	-0.428***	-0.427***
	(0.616)	(0.616)	(0.616)	(0.616)	(0.136)	(0.136)	(0.136)	(0.136)
Black	-0.0836	-0.0956	-0.0833	-0.0848	-0.329***	-0.332***	-0.331***	-0.331***
	(0.560)	(0.560)	(0.559)	(0.559)	(0.121)	(0.121)	(0.121)	(0.121)
BIP	0.235	0.236	0.243	0.238	-0.158*	-0.161*	-0.160*	-0.158*
	(0.397)	(0.397)	(0.397)	(0.397)	(0.0903)	(0.0904)	(0.0903)	(0.0904)
Arab	2.363	2.336	2.327	2.294	-0.362	-0.364	-0.361	-0.359
	(1.943)	(1.948)	(1.944)	(1.948)	(0.231)	(0.231)	(0.231)	(0.231)
Constant	14.48***	14.19***	14.26***	14.32***	4.383***	4.479***	4.444***	4.434***
	(0.912)	(0.911)	(0.912)	(0.911)	(0.218)	(0.218)	(0.218)	(0.218)
Number of observations	47169	47169	47169	47169	36671	36671	36671	36671
Number of individuals	6747	6747	6747	6747	6557	6557	6557	6557

Notes: columns are estimated on each social capital component: (1) corresponds to Social Network support, (2) Personal Relations, (3) Civic Participation, (4) Trust and cooperative norms.
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Errors are clustered at the individual level.

Appendix C

Chapter 4 Appendix

Concentration	Have you recently been able to concentrate on whatever you're doing? 1. Better than usual 2. Same as usual 3. Less than usual 4. Much less than usual
Loss of Sleep	Have you recently lost much sleep over worry? 1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual
Playing a useful role	Have you recently felt that you were playing a useful part in things? 1. More so than usual 2. Same as usual 3. Less so than usual 4. Much less than usual
Capable of making decisions	Have you recently felt capable of making decisions about things? 1. More so than usual 2. Same as usual 3. Less so than usual 4. Much less capable
Constantly under strain	Have you recently felt constantly under strain? 1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual
Problem overcoming difficulties	Have you recently felt you couldn't overcome your difficulties? 1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual
Enjoy day-to-day activities	Have you recently been able to enjoy your normal day-to-day activities? 1. More so than usual 2. Same as usual 3. Less so than usual 4. Much less than usual
Ability to face problems	Have you recently been able to face up to problems? 1. More so than usual 2. Same as usual 3. Less able than usual 4. Much less able
Unhappy or depressed	Have you recently been feeling unhappy or depressed? 1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual
Losing confidence	Have you recently been losing confidence in yourself? 1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual
Believe worthless	Have you recently been thinking of yourself as a worthless person? 1. Not at all 2. No more than usual 3. Rather more than usual 4. Much more than usual
General happiness	Have you recently been feeling reasonably happy, all things considered? 1. More so than usual 2. About the same as usual 3. Less so than usual 4. Much less than usual

C.1 Socio Economic Status

Our socio economic status categorisation is made of four categories: salariat, own account workers, intermediate workers and working class. These variables are a short version of the National Statistics Socio-economic Classification (NS-SEC) of one's current job classification. In particular, each category consists of the following job descriptions:

- Salariat: Employers in large establishments, Higher managerial and administrative occupations, higher professional employees (traditional or new), higher professional self-employed (traditional or new), lower professional or higher technicians employees (traditional or new), lower professional or higher technicians self-employed (traditional or new), lower managerial and administrative occupations and higher supervisory occupations
- Intermediate: intermediate clerical and administrative occupations, intermediate sales and service occupations, intermediate technical3 and auxiliary occupations and intermediate engineering occupations
- Own account workers: Employers in small establishments, own account workers in non professional occupations, own account workers in agriculture
- Working class: semi routine service, sale, operative, agricultural clerical and childcare operations; routine sales and services, production, technical, operative and agricultural operations

Details on the NS-SEC are provided by the Office for National Statistics (ONS), see http://www.ons.gov.uk/ons/gu method/classifications/current-standard-classifications/soc2010/index.html

Appendix D

Chapter 5 Appendix

D.1 Descriptive statistics

Table D.1: Descriptive statistics

Variable	mean	sd	min	max	obs
Government response stringency at the time of the peak	79.59	9.967	46.30	96.30	27
Index of confidence	33.59	13.76	14.29	69.54	27
Confidence in the government	24.98	12.77	8.487	56.34	27
Confidence in the parliament	24.33	15.50	7.270	61.29	27
Confidence in local authorities	40.58	13.90	11.67	66.59	27
Confidence in police	52.32	16.64	22.52	91.10	27
Confidence in the press	26.10	10.29	10.43	61.24	27
Confidence in juridical system	34.45	19.33	10.87	79.61	27
Trust in others	32.37	17.61	9.101	78.62	27
Rate of decrease of new contagions	-6.826	5.336	-22.50	-2.200	19
New deaths at the time of the peak (per one million)	4.242	6.384	0	27.12	27
New cases at the time of the peak (per one million)	62.62	61.67	8.868	265.0	27
Government response stringency one week before the peak	32.12	20.71	0	70.84	27
Total deaths before the lockdown (per one million)	0.821	1.368	0	4.891	27
Total number of ICU beds (per 100,000)	11.90	6.368	4.200	29.20	27
GDP per capita in 2018 (constant 2010 US dollars, log),	10.33	0.617	9.065	11.61	27
Gini index	31.85	3.621	25.40	37.40	27
Expected number of life years with chronic disease	18.59	4.378	9.163	25.88	27
Share of people that rarely meets others	17.55	6.736	7.616	28.77	27

D.2 List of countries

Table D.2: The list of countries available for the analysis varies depending on the dependent variable

Austria	Belgium	Bulgaria*	Croatia*
Cyprus*	Czech Republic	Denmark	Estonia
Finland	France	Germany	Greece
Hungary	Ireland*	Italy	Luxembourg
Netherlands	Portugal	Romania*	Slovakia*
Slovenia	Spain	Sweden	United Kingdom

* Data on speed of decline of new contagions is not available.

D.3 Principal Components Analysis

The PCA explains the variance covariance structure of the variables via linear combinations among them, and its objectives are generally data reduction and interpretation. Table D.3 reports the eigenvalues, who add up to the sum of the variances of the variables in the analysis, i.e. the total variance of the variables. The eigenvectors table (D.4) shows that each component has a similar factor loading, around 0.38, there is no unexplained variance and Rho = 1.00 (not reported). This indicates that all seven components of trust and confidence load similarly in the composition of the confidence index. We then utilize the Cronbach's alpha statistic to build the confidence index out of the seven components we have seen having the same weight. The statistics computes the interim covariances of all variables, which we find equal to 184.563, and the scale reliability coefficient which is 0.9546. Then the Cronbach's alpha generates a summative scale from the utilized components which have in fact almost the same factor loadings and contribute roughly equal information to the score.

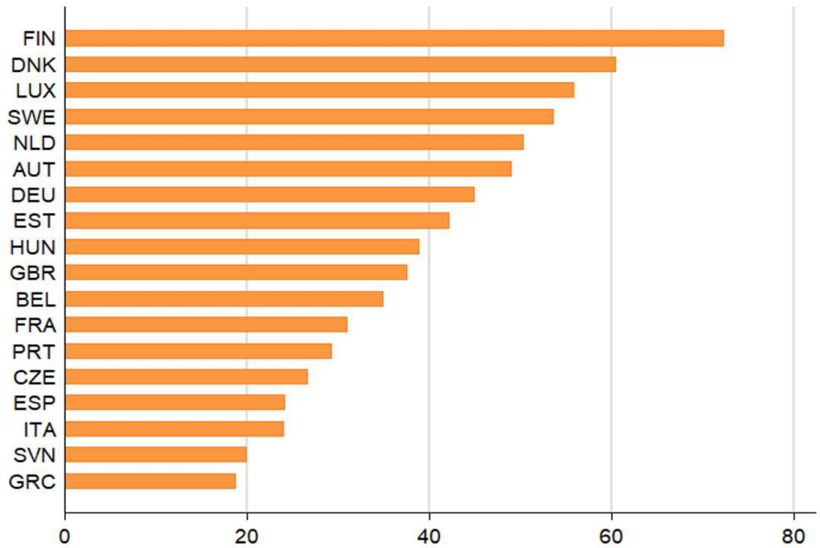
Table D.3: Principal components/correlation

	Eigenvalue	Difference	Proportion	Cumulative
Trust in others	5.57306	4.96316	0.7962	0.7962
Trust in local authorities	.609897	.249217	0.0871	0.8833
Trust in Government	.36068	.0948031	0.0515	0.9348
Trust in police	.265877	.128519	0.0380	0.9728
Trust in press	.137358	.103424	0.0196	0.9924
Trust in judicial system	.0339336	.0147361	0.0048	0.9973
Trust in Parliament	.0191975	.	0.0027	1.0000

Table D.4: Principal components (eigenvectors)

	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Unexplained
Trust in others	.3762374	-.1222118	.6160532	-.4124211	.3319554	.2885711	.3169058	0
Trust in local authorities	.3797146	-.0663725	-.5787159	.2189593	.6554693	.1781435	.084742	0
Trust in Government	.3960443	.1598452	-.3471788	-.1493004	-.6223762	.3822085	.3759512	0
Trust in police	.3665981	-.4053516	.2954157	.6380707	-.2303055	.2385113	-.3113888	0
Trust in press	.3073862	.8286617	.2522926	.3341093	.0697803	-.1966197	.004938	0
Trust in judicial system	.4049941	-.3145648	-.0356096	-.016018	-.1133136	-.7983909	.2919522	0
Trust in Parliament	.405599	.0718846	-.1133279	-.4905662	-.0454275	-.0770278	-.754206	0

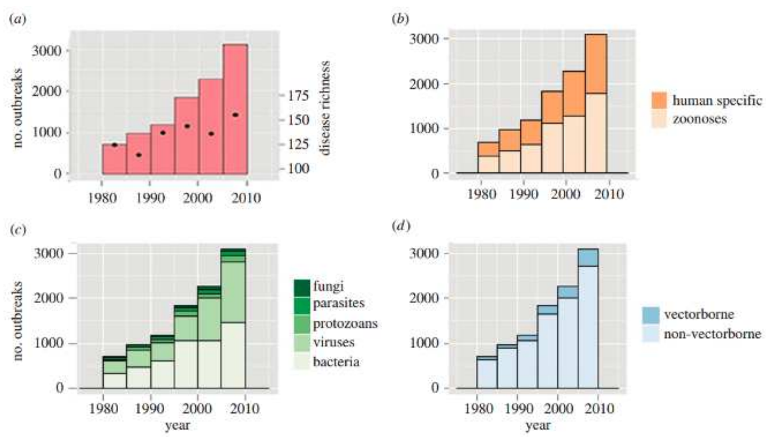
Figure D.1: Confidence levels per analysed country



Source: own elaboration of data from EQLS.

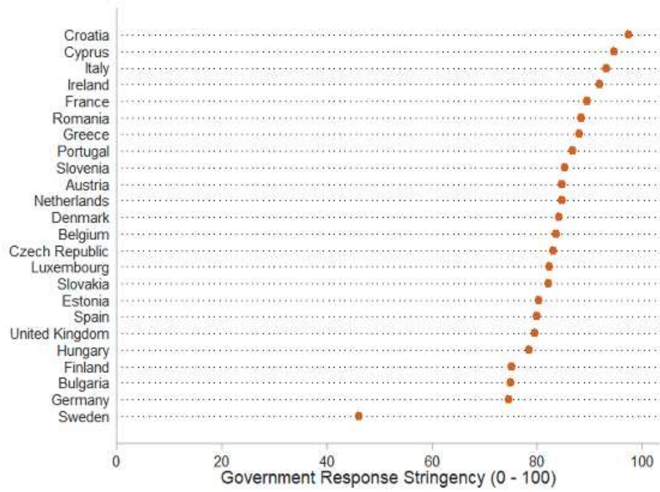
D.4 Figures

Figure D.2: Infectious disease outbreaks



Source: Smith et al., 2014, Global rise in human infectious disease outbreaks, Journal of the Royal Society Interface, Volume: 11, Issue: 101

Figure D.3: Government Stringency by country



Source: Our World in Data, 2020.

Source: own elaboration of data from Our World in Data.