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CONTENTS

Introduction

As a PhD student, I had the opportunity to conduct research in the field of human capital and health economics. This collection of three essays in applied economics presents my contribution to existing research.

Human capital has always been recognized as a driver of improved productivity in the economy; according to Becker (Becker (1964)), it consists of the investment in year of education and vocational training, where the returns on investment are higher expected individual earnings. Subsequently, it was acknowledged that human capital could not be measured solely in terms of years of education, as it is connected to the quality of educational institutions as well as to the abilities of students (OECD (2010); Wößmann (2003); Lockheed & Hanushek (1994); Heckman et al. (2014)). These authors showed the growing importance of quality of education for economic development and vertical mobility and proposed several different ways to evaluate educational institutions (Lockheed & Hanushek (1994); Hanushek (1986); Raudenbush & Willms (1995); Braun & Wainer (2006); Agasisti (2014); De Witte & López-Torres (2017); Masci et al. (2018); Loeb et al. (2018)). Traditional statistical-economic methods used to analyse schooling outcomes are the analyses of efficiency and effectiveness, separately considered. As regards the first, the problems was to maximise monetary school revenues (output) given monetary costs (input); the second is related to the capacity of the school to increase student knowledge measured in terms of CS, linked to abilities to reason, remember, communicate, understand written material, learn new information (Lockheed & Hanushek (1994); Heckman et al. (2014); Atkin (1998); Heckman & Kautz (2012); OECD (2015); Fabbris & Fornea (2019)). More recently, human capital has been also connected to Non-Cognitive Skills, personality resources linked to motivation in learning, relational capabilities, emotional stability and autonomy in pursuing personal objectives. Many authors demonstrated that Non-Cognitive Skills improve the acquisition of Cognitive Skills, linked to abilities to reason, remember, communicate and understand written material (Heckman & Kautz (2012); Cunha & Heckman (2008); Cunha & Heckman (2010); OECD (2017)).

By taking advantage of my direct involvement in a field project, I offer some contribution to the research. The project-leading Professors and I propose a new approach with which to measure school efficiency by including student Non-Cognitive Skills in the analysis. In our framework, we jointly consider efficiency and effectiveness including both Cognitive Skills and Non-Cognitive Skills and propose two analyses. The first is called "Static Non-Cognitive Skills Efficiency" and uses a Stochastic Frontier Approach to measure the efficiency of transforming Non-Cognitive Skills into Cognitive Skills. We are able to show that specific Non-Cognitive Skills positively impact Cognitive Skills and contribute to enhancing school efficiency. The second analysis, defined "Dynamic Non Cognitive Skills Efficiency", assesses the effectiveness of school educational programs aimed at developing Non-Cognitive Skills. We use a Difference-in-Differences model based on a Stochastic Frontier Approach and we observe that these programs (treatment) have a positive effect on Non-Cognitive Skills. Our survey includes 8th grade students attending 25 schools in the Provincia Autonoma di Trento, in Italy. Our results provide new perspective on education in schools, that should be more learning-oriented, aimed at fostering creativity and engagement of students in class and in their educational pathways.

The second research field investigated is health economics. It received a strong boost with the outbreak of COVID-19 pandemic, given that policymakers and public authorities needed evidence-based suggestions to make important decisions regarding public health policies. I offer two contributions, both strictly related to coronavirus pandemic.

First, I reflect on the disruption of formal and informal care due to lockdown restrictions and its impact on elderly's mental health. At the outbreak of COVID-19 contagion, governments worldwide implemented lockdown restrictions to contain the spread of the virus. Although effective in preventing a further dissemination of the virus, these interventions were immensely disruptive to people's social connections and had the repercussions on the healthcare industry and social services (Bu et al. (2020)). Vulnerable groups such as older people encountered unique and remarkable challenges in coping with their care needs without leaving their homes (AgeUK (2020)). In the U.K., elderly support is dependent upon a combination of informal and formal care: statutory-source community care and social services, privately paid care workers, neighbours, friends, and family members (Vlachantoni et al. (2015); Maplethorpe et al. (2015)). The strict restrictions introduced by the U.K. government, together with the reorganization of the healthcare system at all levels, produced a disruption in both types of caregiver activities (Topriceanu et al. (2021)). Existing research paid significant attention to the limited availability of formal care services during the pandemic (Maccora et al. (2020); Rodrigues et al. (2021);

Tsapanou et al. (2021); Leggett et al. (2021); Monteiro et al. (2022); McGarrigle et al. (2022); Costi et al. (2023).

My contribution addresses a relevant, though understudied issue: the connection between disruption of formal care and its potential impact on the elderly population's mental health, and the inter-relationship between formal and informal care disruptions due to lockdown restrictions and older adults' mental-health deterioration, in the U.K context. Data are drawn from the U.K. Household Longitudinal Study, Understanding Society, and the methodology is based on a joint model of informal care and formal care disruption and mental health conditions, considering individual's unobserved heterogeneity that might have characterized this relationship. Findings show that the disruption of informal and formal support represents a significant risk factor for psychological well-being in older adults and increases their risk of depression. The empirical evidence outlines the importance of designing public policies to contain pandemic crises with the realization that some population groups are more affected than others. Hence, these groups need different social restrictions from those imposed on the general population since they may suffer more from the consequences of isolation and reduction in social contacts (Gulland (2020); CarersUK (2020)).

The second contribution is focused on the relation between individual's social interactions and loneliness during the pandemic, as prolonged periods of social isolation may have exacerbated people's feelings of loneliness that, in turn, are connected to a variety of adverse health outcomes. As regards the second issue, i.e., the association between social interactions and loneliness during COVID-19 pandemic, it should be acknowledged that efforts made to protect the population, particularly those at higher risk, raised concerns on the potential adverse impact of these restrictions on people's overall well-being (Brooks et al. (2020)). Stay-at-home orders and social isolation from friends and family members caused stronger feelings of loneliness that in turn led to heightened symptoms of depression (Krendl & Perry (2020)). In fact, while being important per se, as it relates to human wellbeing, loneliness is associated with multiple negative health outcomes, resulting in increasing morbidity and mortality (Hawkley & Cacioppo (2010); Steptoe et al. (2013); Gale et al. (2018); Jarach et al. (2021); Wenger et al. (1996)). While social isolation and loneliness are distinct concepts (Russell et al. (1980)), research has shown that they are closely linked, with social isolation often serving as a precursor to feelings of loneliness (?; ?). Thus, There have been calls to ascertain how the COVID-19 pandemic has affected loneliness (Armitage & Nellums (2020); Banerjee & Rai (2020)).

Results offer some first evidence on the link between pre-pandemic social interactions and the impact of COVID-19, and of the restrictions implemented by the governments to limit its spread among the population, on the sentiment of loneliness. Two research questions are investigated: the first discusses if neighbourhood social cohesion is a protective factor for loneliness; the second tries to understand how certain characteristics of people's social networks (i.e., close ties and mode of communication) impact loneliness. By relying on numerous waves of data from the U.K. Household Longitudinal Study, longitudinal models are constructed to assess the effect of neighbour social cohesion and social relations indicators on loneliness, before and during the pandemic. Findings contribute to a better understanding of the protective role of neighbour and social relations against loneliness during coronavirus emergency and suggest some policy implications. As social cohesion in the neighbourhood where one lives appears to be an important moderator of loneliness, even in times of pandemic, social policies at the local level should increase opportunities for interaction in neighbourhoods. Moreover, if public authorities need to adopt policies restricting social relations in the future, they should design forms of restriction at local level taking into account the importance of social relations.

The rest of the thesis is structured as follows. The first chapter, entitled "Cognitive Skills and Non-Cognitive Skills to measure school efficiency" is co-authored with Professor Giorgio Vittadini, the scientific head of the field project and Professor Giuseppe Folloni. It discusses a new approach with which to measure school efficiency, by including Non-Cognitive Skills and Cognitive Skills in the analysis. The second chapter ("The Impact of Informal and Formal Care Disruption on Older Adults' Psychological Distress During the COVID-19 Pandemic in the UK") is co-authored with my PhD supervisor, Professor Cinzia Di Novi (University of Pavia and European Commission, Joint Research Centre - JRC) and Professor Gianmaria Martini (University of Bergamo). It evaluates how formal and informal caregiving disruptions – due to the U.K. government's non-pharmaceutical interventions (NPIs) aimed at reducing transmission of the virus – may have affected the likelihood of psychological distress among the elderly. The third chapter entitled "The association between neighbour cohesion, social relations and loneliness during COVID-19: evidence from England" is co-authored with Professor Cinzia Di Novi (University of Pavia and European Commission, Joint Research Centre - JRC), Professor Gianmaria Martini (University of Bergamo) and Dr. Piera Bello (University of Bergamo). It discusses the relation between neighbourhood social cohesion, social relations and loneliness during COVID-19 pandemic. Each chapter can be read separately, as they are stand-alone articles with their own introduction and conclusion. For a better reading, figures and tables are cited in the text and can be found at the end of each chapter, as well as appendices and references.

Although the three chapters address research questions on different topics, a common theme can be traced. In the first chapter, Cognitive and Non-Cognitive Skills are included in the model to measure school efficiency and effectiveness; in the second, emphasis is placed on elderly's mental health, to assess the impact of the disruption of care; in the third, the focus is on individuals' feelings of loneliness and how these might have been exacerbated by the pandemic. Behavioral and psychological features of surveyed individuals are characteristic elements of all three eassys, with an attempt to provide a comprehensive and transversal look at different economic issues.

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1.NON-COGNITIVE SKILLS AND COGNITIVE SKILLS TO MEASURE SCHOOL EFFICIENCY

Abstract

We propose a new approach with which to measure school efficiency by including student Non-Cognitive Skills in the analysis. In classical analysis, efficiency is measured separately from effectiveness. In our framework, we jointly consider efficiency and effectiveness, including both Cognitive Skills and Non-Cognitive Skills. We call our approach “Non-Cognitive Skills Efficiency” and we propose two analyses. The first is called “Static Non-Cognitive Skills Efficiency” and measures the efficiency of transforming Non-Cognitive Skills into Cognitive Skills, by means of a Stochastic Frontier Approach. We verify that some Non-Cognitive Skills have effect on Cognitive Skills and contribute to increase school efficiency. The second is defined “Dynamic Non-Cognitive Skills Efficiency” and measures the efficiency of school educational programmes aimed at improving Non-Cognitive Skills. The statistical method is a Difference-in-Differences model based on a Stochastic Frontier Approach. We find that these educational programmes (treatment) have a positive effect on Non-Cognitive Skills. The survey concerns 8th grade students attending 25 schools in the Provincia Autonoma di Trento, in Italy. The dataset comprises both survey data and the administrative data of local authorities, thus providing a complete set of information at student level on Cognitive Skills and Non-Cognitive Skills skills, social capital variables, in particular the socioeconomic background of families, and teaching parameters. We measure school efficiency at class level, because this level is less affected by unobserved environmental factors. The results provide new perspectives on education in schools.

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1.1 Introduction

The classical approach to the analysis of schooling outcome is, in the economic field, the Human Capital (HC) approach. For decades, HC was measured in economic theory by using a variety of methods (Folloni & Vittadini (2010)); whatever approach was followed, HC has always been recognized as a driver of improved productivity in the economy (see for instance the production function approach of Mankiw, Romer and Weil (Mankiw et al. (1992)) and other endogenous growth models). According to Becker (Becker (1964)), HC consists in particular of the investment in years of education and vocational training, where the returns on investment are higher expected individual earnings.

Subsequently, it was seen that HC could not be measured solely in terms of years of education, because it is related to the quality of educational institutions as well as to the abilities of students (Atkin (1998); Wößmann (2003); Lockheed & Hanushek (1994); Heckman et al. (2014)). These authors showed the growing importance of quality of education for economic development and vertical mobility. Consequently, in recent decades, the literature has put forward several different ways to evaluate educational institutions (Lockheed & Hanushek (1994); Hanushek (1986); Raudenbush & Willms (1995); Braun & Wainer (2006); Agasisti (2014); De Witte & López-Torres (2017); Masci et al. (2018); Loeb et al. (2018); see also the special issue of the Journal of Educational and Behavioural Statistics, 2004).

Various questions have become important, such as: What are the goals that schools today, in light of current changes, must achieve? What are the teaching/learning methods best suited to achieving these goals? How can we verify that the goals are being pursued and achieved? The traditional statistical-economic methods used to answer the foregoing questions are the analyses of efficiency and effectiveness, separately considered.

In classical efficiency analysis, the problem was to maximise monetary school revenues (output) given monetary costs (input). Effectiveness was the capacity of the school to increase student knowledge measured in terms of Cognitive Skills (CS), linked to abilities to reason, remember, communicate, understand written material, learn new information, (Lockheed & Hanushek (1994); Heckman et al. (2014); Atkin (1998); Heckman & Kautz (2012); OECD (2017); Fabbris & Fornea (2019)).

In the research reported in this paper, we first adopt a more recent approach where efficiency and effectiveness are considered jointly (De Witte & López-Torres (2017)). Efficiency- Effectiveness is connected to a broader and more complete definition of HC which includes the capacity of schools and universities to achieve an increase in student skills, measured in terms of CS.

Secondly, we innovatively measure efficiency-effectiveness not only in terms of CS but also of Non-Cognitive Skills (NCS). NCS potentially affect goal-directed effort, healthy social relations, adequate judgement and decision-making, and can be improved by means of suitable educational programmes (Heckman et al. (2014)).

Therefore, the first research question is: do NCS affect school efficiency measured in terms of CS? To answer this first question we define "Static NCS Efficiency" where NCS and initial CS are the inputs while final CS are the outputs. The statistical method we will use is the Stochastic Frontier Analysis (SFA).

The second research question is: are specific educational actions implemented by schools able to increase student NCS? To answer this second question we define "Dynamic NCS Efficiency" where NCS are both inputs and outputs. The statistical method that we use is a causal version of SFA in a Difference-in-Differences (DiD) framework.

We apply our method to a panel sample of students attending school in the Provincia Autonoma di Trento (PAT), an autonomous region with special statute in northern Italy. Our dataset combined PAT survey data and administrative data, providing detailed information on student CS levels, a complete set of students' NCS constructs, with information on family background and teaching characteristics. Information was collected from students in the last year – the fifth - of Italian primary school, and the last year – the third – of Italian middle school, which we have called the 5th and 8th grades. School efficiency is measured at class level, because it is less affected by unobserved environmental factors.

The paper is organized as follows: section 1.2 briefly surveys the literature on the traditional efficiency and effectiveness of educational institutions; section 1.3 describes SFA and DiD-SFA methods, as used in the analysis. Section 1.4 describes how the dataset was constructed. Section 1.5 sets out the results with some comments. Section 1.6 concludes.

1.2 Conceptual background

A general definition of educational efficiency and effectiveness is given by Lockheed and Hanushek (Lockheed & Hanushek (1994)). External effectiveness compares educational institutions of middle and high school level or tertiary level, according to students' employment characteristics (see for example Becker (1964); Fondazione Agnelli (2018); AlmaLaurea (2019)). External efficiency measures either long term HC returns – over the lifecycle, that part of expected income related to CS acquired through education (Becker (1964)) - or short term HC returns – that part of expected income in the first years after the diploma or the degree related to CS acquired through education (Lovaglio & Vittadini (2008); Lovaglio & Vittadini (2014)). Internal efficiency is usually measured by a cost-benefit analysis based on monetary quantities (Mouter et al. (2021)). Internal effectiveness compares educational institutions to students' average CS, taking their characteristics into account (see for example (INVALSI (2016); OECD (2019)).

The educational process is analysed by means of a production function where inputs and outputs are measured at student or institution level. Depending on which input and output variables are considered, the analysis seeks to capture either educational efficiency or effectiveness. However, studying efficiency separately from effectiveness is reductive, because the efficiency of a school must be verified together with its effectiveness, that is, its ability to educate.

In particular, De Witte and López-Torres (De Witte & López-Torres (2017)) state: "Efficiency (meaning doing things right) in education should not be seen separately from effectiveness (meaning doing the right things) and value for money. Since the results of the education process are social constructs, there is always an effectiveness frontier, that is an acceptable level of the desired outcomes, which may be realized." (p. 339). An approach that contemporaneously takes into account efficiency and effectiveness seems more complete because it considers all the dimensions of education and how these dimensions evolve and mature in the school process. In fact, if it is true that a school or university is a business that must evaluate its economic sustainability, it is also true that unlike productive businesses, the result has to do with improving the level of education of students.Therefore, many authors analyse school efficiency and effectiveness jointly (De Witte & López-Torres (2017); Masci et al. (2018); Titus (2006); Powell et al. (2012);

Cherchye et al. (2015)).

In efficiency-effectiveness analysis outcomes are measured in terms of CS at the end of schooling, assessed in terms of standardized achievements, graduation rates, pass rates or average test scores [11]. Inputs are CS at the beginning of the school year and other student characteristics such as psychological and behavioural variables, demographics, family-related variables (De Witte & López-Torres (2017)). CS today are measured by various forms of standardised achievement tests (see for instance the Progress in International Reading Literacy Study (PIRLS), started in 2001; the Trends in International Mathematics and Science Study (TIMMS) started in 1995; the Programme for International Student Assessment of the OECD (PISA), started in 2000). This allows to avoid the risk of bias due to the subjective evaluation of teachers or schools.

More recently, HC has been also connected to NCS, which are personality resources linked to motivation in learning, relational capabilities, emotional stability, autonomy in pursuing personal objectives. Many authors showed that NCS improve the acquisition of CS (Heckman & Kautz (2012); Cunha & Heckman (2008) Cunha & Heckman (2010)). Building on and extending recent findings on NCS and CS, we propose a new version of the efficiency-effectiveness approach, which we have called NCS efficiency.

The first question covered by our research analyses whether NCS and CS possessed by students at the beginning of the scholar period affect school efficiency, measured in terms of final CS. We quality our results by the use of properly selected control variables (socio-economic and demographic characteristics). To answer to this question we propose a "static NCS efficiency" approach, based on a SFA, where NCS are used as input variables. This first approach provides a new vision of educational added value theory (Braun & Wainer (2006); Bryk & Weisberg (1976)) which measures the knowledge contribution that a teacher, class and school make to students' CS. We evidence that educational added value does not only measure the increase of CS, but also the ability to transform NCS into final CS.

The second question covered by our research enquires the causal impact of educational programmes targeted to improve students' NCS. The relevance of this question stems from the fact that NCS can be considered not only as inputs to the educational process but also as very relevant outputs, depending on how, in concrete, the educational programs are implemented to improve and leverage on them. To answer this question we propose a "dynamic NCS efficiency" approach based on a causal version of SFA in a Difference-in-Differences (DiD) framework, where NCS, measured before the provision of educational programs, are used as input variables, together with initial CS and other control variables, while NCS, measured after the provision of programmes, are outputs. The two approaches give a comprehensive and complete picture of the importance of NCS to the study of school efficiency.

1.3 Method

1.3.1 Static NCS Efficiency: Stochastic Frontier for including NCS among inputs

In the late 1970s two classes of models, Data Envelopment Analysis (DEA) (Charnes et al. (1978); Charnes et al. (1981)) and Stochastic Frontiers (SFA) (Aigner et al. (1977); Meeusen & van Den Broeck (1977); and (Battese & Corra (1977)) were developed to estimate the efficiency of organisational units (also called decision-making units -DMUs - or firms). These models adopt two alternative approaches: DEA is a non-parametric method, while SFA analysis is parametric. Both methods were developed to estimate the efficiency of organisational units, such as schools, healthcare institutions and firms, and use the same set of inputs to produce the same set of outputs. DEA is based on linear programming which takes the observed input and output values and, solving an optimisation problem, calculates a production possibility set (PPS) under certain assumptions (free availability of inputs and outputs, convexity, scaling and additivity: see Bogetoft & Otto (2011); Banker et al. (1984)). The distance of a DMU from the frontier is then used as a measure of its inefficiency. This method measures efficiency in relation to the best DMU practice.

The SFA model, on the other hand, uses observed input-output correspondences to estimate an underlying relationship between the inputs and outputs. This function is then used as the frontier against which to measure the efficiencies. It was developed to introduce random factors by fitting a production function, and allowing the frontier to shift around the fitted function for individual companies. To do this, a composed error term is used, split into a one-sided error term measuring firm-specific inefficiency and a two-sided error term showing random fluctuations, which is identically and independently distributed across firms.

DEA and SFA have the following characteristics: First, SFA allows random noise to be incorporated into the model, whereas DEA is deterministic, i.e. it assumes there is no random noise in the data. This is a very large assumption: any statistical noise, measurement errors, luck, omitted variables and other misspecifications are counted as inefficiency. Hence, the distance of a DMU from the efficiency frontier is interpreted as inefficiency. However, a measurement error or other sources of noise (i.e. outliers) may influence the shape and position of the frontier. Deviations from the frontier may also be the result of noise in the data and not only technical inefficiency (Masci et al. (2018); Coelli et al. (2005); Kumbhakar & Lovell (2000)). Unlike DEA, SFA includes two random components of the error term to account for inefficiency, noise and measurement errors.

Second, since DEA is good at estimating "relative" efficiency, its measurements are only valid in the sample investigated. Conversely, SFA can be used to conduct statistical tests concerning both conventional hypotheses and any parameter restrictions associated with economic theory (Coelli et al. (2005)). Hence its estimates may be extended to other data samples. Third, SFA can be used to identify persistent and time-invariant inefficiency when dealing with panel data.

Fourth, however, a key concern with a major role in the economics and management literature has been overlooked in the DEA literature: the presence of endogeneity (Angrist & Pischke (2014)). In the statistical framework, endogeneity arises when the assumption that all inputs or covariates are uncorrelated with the error term does not hold (Angrist & Pischke (2014); Greene (2003)). The econometrics literature provides suitable techniques to correct the potential identification problems arising from endogeneity. However, in the DEA environment, this concept involves feedback from the achieved output to the inputs devoted to the activity (Orme & Smith (1996)). Some studies (Orme & Smith (1996); Bifulco & Bretschneider (2001); Peyrache & Coelli (2009)) using Monte Carlo simulation techniques comparing DEA and SFA, show that the estimates of inefficiency obtained with the former method may be severely biased. Finally, the education sector is one where positive endogeneity very frequently arises due to the school self-selection problem ((De Witte & López-Torres (2017)); Schlotter et al. (2011); Webbink (2005)) "Endogeneity arises when inputs are correlated with v or u (i.e. inefficiency and random noise parameters) or both. This can occur when there is feedback from either statistical noise or inefficiency to the choice of inputs, or when the inputs influence the level of inefficiency as well as the frontier. Endogeneity needs to be dealt with because the usual procedures for estimating SF models depend on the assumption that the inputs are exogenous" (Amsler et al. (2016), p.280).

In our case, the inputs that might suffer from endogeneity due to correlation with the parameter of inefficiency include the variables describing school and faculty characteristics, such as teacher salaries and work commitment, the level of use of laboratories and classrooms, revenues and costs. Clearly, such factors may be related to the degree of efficiency of schools, because they might determine, or be determined by, efficiency. On the other hand, inputs might suffer from endogeneity due to correlation with the random noise parameter when they can be NCS covariates were measured after CS, there could be endogeneity.

Fifth, SFA studies the impact of environmental variables as determinants of inefficiency using a single equation estimator approach. DEA can deal with environmental variables only by using a two-stage approach: the first stage with DEA estimates and the second, with a tobit regression, using DEA efficiency scores as dependent variable. However, as shown by Simar and Wilson (Simar & Wilson (2007)), this two-stage approach leads to biased estimates of the impact of environmental variables.

Given the above discussion, we favour SFA to estimate the impact of CS and NCS in education. In our use of SFA, final CS are the outputs defining the frontier and NCS are the inputs. The control variables are the initial CS and socio-economic and demographic variables describing student characteristics. We decided to compute school efficiency at the class level, because it is less affected by unobserved environmental factors. Hence, the model has the following structure (Aigner et al. (1977); Battese & Coelli (1992); Greene (2005)):

$$y_{ij} = \alpha + \lambda k_j + \sum_{h=1}^{m} \beta_h x_{hij} - u_{ij} + v_{ij} \tag{1.1}$$

where $i = (1, ..., k_j)$ classes in the j-th school; $j = (1, ..., n)$ schools;

$h = (1, ..., m)$ control variables;

y_{ij} average CS values for the i-th class of the j-th school;

α intercept;

k_j school effect;

x_{hij} average i-th class of the j-th school value of NCS or control variables;

u_{ij} time-invariant stochastic inefficiency of the i-th class of the j-th school;

v_{ij} stochastic disturbance.

U_σ module of variance of time-invariant stochastic inefficiency (u_{ij}), expressed in terms of natural logarithm; V_σ variance of stochastic disturbance (v_{ij}) expressed in terms of natural logarithm;

$$\gamma = \frac{exp(U_\sigma)}{exp(U_\sigma + V_\sigma)} \tag{1.2}$$

where γ is the average relative weight of the time-invariant stochastic inefficiency over the total variance. It shows the importance of time-invariant stochastic inefficiency with respect to stochastic disturbance.

We also assume (Arellano-Valle & Azzalini (2006); Gonzalez-Farias et al. (2004)):

1. the random vectors u_{ij}, v_{ij} are independent in probability;

2. for every i, j, u_{ij} has a half normal distribution with zero expected value and variance s^2 left-truncated at zero;

3. for every i, j, v_{ij} has a normal distribution with zero expected value and variance σ^2 .

The three assumptions (1)–(3) allow the use of a maximum likelihood (ML) estimation approach for an SFA model with this specific distribution. We have not used a more elaborate SFA model based on time-varying inefficient parameters because it would require observations for additional time periods, which we do not have. To avoid estimation and computational problems for SFA with many covariates, we have adopted a stepwise strategy including only the best performing covariates for the final estimation.

Moreover, in order to avoid the possible effects of a small sample size, we carried out a bootstrap analysis, using the estimated values of coefficients from our initial sample including random effects to compute new values for the dependent CS, replicating this procedure 500 times. Finally, we compared estimated with initial quantities, and derived new estimates, corrected for possible bias and the 95% bootstrap confidence intervals (Faraway (2005); Colombi et al. (2014)).

1.3.2 Dynamic NCS Efficiency: DiD-SFA for assessing the impact of educational programs on students NCS

The second research question deals with educational programmes (here termed "treatment") whose purpose is increasing NCS. Are such programmes capable to improve in causal terms efficiency-effectiveness measured in terms of NCS in those lasses/schools in which they are activated? To answer this question we decided to use a Difference-in-Differences approach (DiD) in connection with SFA, for the following reasons.

First, we take into account the heterogeneity of schools or classes that adopt or do not adopt the educational programmes. The heterogeneity of students' characteristics in treated and non-treated groups was already observed by some educational efficiency researchers (De Witte & López-Torres (2017); De Witte & Van Klaveren (2014)). For example, there are students with more favourable background characteristics such as ethnicity, better educational level of the parents or higher intelligence who tend to self-select in better schools or with better teachers. In randomized studies and experimental settings, techniques for estimating causal effects can resolve this heterogeneity, which may affect the evaluation of educational treatments (Torgerson et al. (2013)).

Second, we consider this heterogeneity connected to the nonexperimental setting of our research. With cross-sectional data, some methods have been proposed "to assess the influence of a treatment without reduced bias from confounding variables" (De Witte & López-Torres (2017)): matching methods (Imbens & Angrist (1994)), weighting methods (Robins et al. (2000)), propensity scores method (see, among others, Guo & Fraser (2014); Imbens, 2000 (Rosenbaum & Rubin (1983)); kernel method (De Witte & Van Klaveren (2014)).

Third, the heterogeneity connected to the nonexperimental setting is analysed with panel data. With panel data, the focus is on the study of the effect of the policy or treatment on certain outcomes of interest as well as on the evolution of such an effect across time on different subpopulations of interest (see, among others, Aalen et al. (2012)).

The more general causal inference statistical technique in observational studies with panel data is DiD (Rubin (1978); Holland & Rosenbaum (1986)). DiD is a simple and effective method to eliminate control variables that influence in heterogeneous ways both the dependent and independent variables, causing a spurious association. DiD replicates a quasi-experimental design for treatment and control groups to obtain appropriate counterfactuals to estimate a causal effect.

DiD is able to additively separate the effects of the control variables from that of the treatment on the expected value of the potential outcomes (Imbens & Angrist (1994)). It is based on the following properties (Lechner et al. (2011)) that we respect in our approach. Stable Unit Treatment Value Assumption (SUTVA): the treatments are completely represented without significant interactions between the members of the treated and not treated schools. Exogeneity (EXOG): control variables are collected before the educational programme and therefore are unaffected by the treatment. No Effect on the Pre-treatment Population (NEPT): the educational programme does not affect students before being managed. Common Trend (CT): with no treatment, the difference between treated and untreated units is assumed to be constant over time. The assumption always holds when control variables are time invariant, as it is in our model. COmmon SUpport (COSU): each student has a positive probability of receiving the treatment. In our approach there is no reason why, a priori, one student should receive the treatment while others should not.

Following Lechner (Lechner et al. (2011)), when these conditions hold, DiD identifies a causal effect called Average Treatment Effect (ATET). ATET is the difference of the differences between the mean outcomes of treated and control groups before and after the treatment, depending on X.

$$y_{ijt}^{(0)} = \alpha + \lambda k_j + \gamma D^{(0)} + \beta x_{ij} - u_j + v_{ijt} \tag{1.3}$$

$$y_{ijt}^{(1)} = \alpha + \lambda k_j + \gamma D^{(1)} + \beta x_{ij} - u_j + v_{ijt} \tag{1.4}$$

where

$i = (1, ..., n)$ classes; $j = (1, ..., q)$ schools;

t =0 time before treatment, t=1 time after treatment

y_{ijt} average NCS values for the i-th class of the j-th school at time t;

$y_{ijt}^{(0)}$ with no treatment; $y_{ijt}^{(1)}$ with treatment;

α intercept;

k_j school effect;

D dummy variable for treatment: $D^{(0)} = 0$ no treatment; $D^{(1)} = 1$ treatment

x_{ij} average value of control variables for the i-th class of the j-th school;

u_j time-invariant stochastic inefficiency of the j-th school;

v_{ijt} stochastic disturbance

and

$ATET_1 = \gamma$

1.4 The dataset: joining the INVALSI dataset with an NCS survey

The sample analysed consisted of 1522 8th grade students attending schools in the Provincia Autonoma di Trento (PAT), in Italy. The sample was collected as follows: during the 2017–2018 school year, IPRASE [1], the regional authority for research on education and schooling, launched a project to evaluate student Non Cognitive Skills. 25 middle schools with a total of 108 classes (out of 77 PAT middle schools and a total of 5502 students) joined the research project on a voluntary basis. 12 schools (with a total of 845 students) carried out curricular educational programmes aimed at improving student NCS. This enabled us to measure the effect of these activities in fostering NCS, through a Difference- in-Differences approach. The integrated dataset consisted of five datasets, which were matched by IPRASE and INVALSI[2] (see Appendix for details). Therefore, the final dataset contained both survey data and PAT administrative data at the student level, with a longitudinal dimension.

The first four datasets were the following:

- INVALSI 2015 questionnaire providing student scores from standardised tests on

[1]Istituto Provinciale per la Ricerca e la Sperimentazione Educativa della Provincia Autonoma di Trento, a public agency founded in 2007 and run under the supervision of the Ministry of Education with the aim of evaluating student skills in reading and mathematics. Standardised tests are administered at the end of the second and fifth years of primary school, at the end of the first and third year of lower secondary school and at the end of the second year of upper secondary school.

[2]INVALSI (Istituto nazionale per la valutazione del sistema educativo di istruzione e di formazione) is the Italian National Institute for the Evaluation of the Education System. INVALSI was established to evaluate the level of competence achieved by students during their years in full-time education, as well as the role of schools in determining those results. INVALSI developed standardized tests to assess students at various stages in their education, which have been used since 2007/2008. The new evaluation system was almost fully implemented by 2011/2012, with the tests being set the end of the second and fifth years of primary school, at the end of the first and third years of middle school and at the end of the second year of high school.

Italian and Maths, NCS and social capital variables at 5th grade

- INVALSI 2018 questionnaire providing student scores from standardised tests on Italian and Maths at 8th grade;

- PAT 2018 Questionnaire on Non-Cognitive Skills [71], a survey specifically designed for the IPRASE research project providing student NCS levels and a set of social capital variables at 8th grade. The survey questions and related NCS indicators followed validated scales taken from the psychological literature.

- PAT 2018 data warehouse providing administrative data related to demographic variables

By means of anonymous identifiers, these datasets were matched in compliance with privacy regulations. Table 1.4 shows the integrated dataset. The variables considered are dichotomous or ordinal. Cognitive Skills were measured by INVALSI standardised tests. These tests are graded at the national level by assessors rather than teachers, guaranteeing transversal comparability of performance. Non-Cognitive Skills, as measured in 2018, are presented here.

The so-called BIG5 model identifies five distinct personality dimensions (John et al. (1999); Heckman et al. (2014); Fabbris & Fornea (2019)). They are: openness to experience, the tendency to be open to reality and new aesthetic, cultural, or intellectual experiences; conscientiousness, the propensity to be organized, responsible, and hardworking; extraversion, the positive orientation of one's interests, energies and affect toward the outer world of people and things; agreeableness, the disposition to act in a cooperative, unselfish manner; emotional stability, predictability and consistency in emotional reactions, with the absence of rapid mood changes.

A more concentrated version of BIG5 is BIG3: inner stability (openness and conscientiousness), relational stability (extraversion and agreeableness) and emotional stability. Other personality dimensions are included among NCS in the literature. Psychological capital (PsyCap) is defined as a positive psychological state of development able to provide competitive advantage (Fabbris & Fornea (2019); Luthans & Youssef-Morgan (2017)); it includes self-efficacy in executing tasks and in achieving goals (Fabbris & Fornea (2019); Avey et al. (2011)) as well as optimism about succeeding now and in the future (Fabbris

& Fornea (2019)). Learning orientation is the propensity to increase personal ability, and Performance orientation is the desire to achieve specific goals and performances (Youssef-Morgan & Luthans (2013)). Self-regulation of motivation to study concerns the reasons that induce people to engage in tasks (Luthans & Youssef-Morgan (2017)). BIG5, BIG3 and Psychological capital are NCS particularly connected with personality growth; Learning orientation, Performance orientation, and Self-regulation of motivation to study are NCS especially related to school achievement.

Non-Cognitive Skills, as measured in 2015, comprised bullying (Bullying carried out 2015, Bullying suffered 2015), quality of class relations (Class relations 2015), anxiety during INVALSI test 2015 (Anxiety 2015), student skill awareness (Italian self-concept 2015, Maths self-concept 2015), motivation (Motivation 2015), external support for studying (Support for studying 2015), wellbeing at school (Wellbeing 2015), and student attitude to learning (Performance oriented 2015, learning oriented 2015). The NCS variables in INVALSI 2015 were connected to NCS variables in PAT 2018 NCS as described in Table 1.3. From a statistical point of view, NCS may be interpreted as latent variables underlying observed items obtained from student replies to the NCS survey. Latent variables can be obtained by means of a confirmatory factor analysis, which may be nonlinear (Heckman et al. (2014); Cunha & Heckman (2010); Cunha & Heckman (2007); Heckman et al. (2009)).

Some of the psychological and behavioural inputs described by De Witte and López-Torres (De Witte & López-Torres (2017)) can be redefined utilising the concept of social capital. Social capital is generally defined as a set of outcomes describing the level of trust, interpersonal and intergroup relationships, and community norms, which influence how individuals react to, and interact with, the surroundings. One of the most interesting and classical definitions of social capital is given by Coleman (Coleman (1988)): “It is not a single entity but a variety of different entities, with two elements in common: they all consist of some aspect of social structures, and they facilitate certain actions of actors - whether persons or corporate actors - within the structure” (see also Aguilera (2002); Heineck & Anger (2010); Fabbris & Favaro (2012)). In our framework, actors are persons (students) and social capital means “an individual resource that consists of the networks of relations of the focal subject that bring it a set of instrumental and expressive resources” (Membiela-Pollán & Pena-López (2017); see also (Glaeser et al. (2002)).

Hence the behavioural and family-characteristic inputs, net of previous achievement results, as put forward by De Witte and López-Torres (De Witte & López-Torres (2017)) are "social capital variables". In this paper they are classified as: student free time activities, student perception of teaching quality and family characteristics. In particular, social capital variables were investigated in the 2018 NCS survey through: 8 questions on students use of free time, asking them to declare how many hours a day/week they devoted to various activities; two variables capturing teaching style, distinguishing between conventional class management and a more challenging way to interact with students (challenge, management); the socio- economic ESCS index, based on wealth, employment status and the educational level of the parents of students. Therefore, specific variables directly regarding parental employment status and educational level were not used, to avoid redundancies.

Other variables took into account student demographics: male (1 if male, 0 otherwise), Italian parent (1 if the student had at least one Italian parent, 0 otherwise), high school (1 if classical or scientific high school, 0 if vocational high school), kindergarten (1 if student attended kindergarten, 0 otherwise), full time (1 if full time, 0 otherwise), Adige Valley (1 if the school was located in the main towns in the Adige Valley, 0 in more remote valleys). Summing up, our integrated panel dataset comprised NCS measures according to a multidisciplinary theory, at 5th grade (2015) and 8th grade (2018); and CS levels from INVALSI 2015 and 2018 standardised scores. We controlled for coding errors and missing data. The fifth data set is PAT 2018 Report on Educational Programmes, presenting educational activities aimed at improving student NCS provided by schools over three consecutive school years (from 2015 to 2018). These educational projects have two types of goal. First, they focus on NCS related to the educational path: Learning orientation, Performance orientation, School motivation, External support for studying, Self-efficacy. Second, they seek to obtain the full development of student personalities, such as BIG3 (inner stability, relational stability, emotional stability) and optimism.

1.5 Results

1.5.1 SFA including NCS as inputs into efficiency analysis

Given the voluntary participation of schools in the survey, the sample may have been non-random. To verify the absence of self-selection, generating bias, we checked for characteristics that may have determined their participation (for instance, more or less CS; better or worse socioeconomic conditions). We tested sample randomness by means of a t-test of the difference between the average of the two groups, (1) participating schools and (0) non-participating schools, computed on CS scores. The variables of interest were INVALSI 2018 scores in Italian and Maths at school level (see Table 1.1 and Table 1.2). In both cases, the differences in average scores between the two groups were not statistically significant at the 90% level (p-values 0.1153 and 0.1104, respectively). As suggested by the literature (Cunha & Heckman (2007); Heckman et al. (2009); Heckman et al. (2014)), each 2015 and 2018 NCS was obtained by means of a confirmatory factor analysis, starting from INVALSI and PAT questionnaires consisting of ordinal items. NCS were measured as latent variables underlying observed items obtained from student replies to the survey. Table 1.5 presents descriptive statistics; the results of the SFA model are set out in Tables 1.6–1.8.

SFA does not suffer from endogeneity, which might arise due to the correlation of inputs with inefficiency parameters, because covariates only regard student characteristics uninfluenced by school inefficiencies and collected earlier that test results. In SFA the covariates are in at least at 5%. The variance of time-invariant stochastic inefficiency parameters (Usigma) is significant, and γ relative weights have good values for both CS Italian and Math 2018. This suggests that there are considerable differences among classes in terms of technical inefficiency. Figs. 1.1 and 1.2 show the inefficiency coefficients of the SFA model for the 108 classes, for Italian and Maths. Parameters are displayed from the least to the most inefficient classes. We focus on the lowest and highest decile of classes and consider mean values of covariates in order to understand the differences between the most and least efficient classes. The most efficient classes have higher means for INVALSI Italian 2015, ESCS and Italian parents than less efficient classes (Tables 1.7 and 1.8).

The main results concerning covariates of the SFA model are, first, NCS related to student personalities have a definite positive effect on CS 2018: inner and emotional stability have positive relations with CS in both Italian and Maths; optimism 2015 with CS in Maths 2018; anxiety (the opposite of emotional stability) during the 2015 INVALSI test has a negative link with CS in Italian 2018. These results are aligned with Heckman's most recent findings (Heckman et al. (2014)). Second, Learning orientation 2015, Performance orientation 2015, Maths self-concept 2015, the NCS most closely connected to school achievement, have a definite positive effect on CS in Maths 2018, showing the importance of a child's determination to perform better.

Third, among the social skills variables, doing homework has a positive relationship with CS in Italian 2018, showing that personal commitment improves school results. Fourth, INVALSI 2015 Italian and INVALSI 2015 Maths have a clear connection with INVALSI 2018 Italian and INVALSI 2018 Maths, respectively, highlighting how crucial primary school education is for the acquisition of CS (see Heckman et al. (2014))

Fifth, as expected, ESCS (concerning the higher level of education of parents and a family's higher socio-economic standing) and Italian nationality, improve student results, demonstrating that initial inequalities are not completely corrected by the education system in Trentino. Sixth, the solid positive connection of kindergartens with both Italian and Maths 2018 CS demonstrates the importance for learning of the first years of life, as affirmed by all the literature (Heckman et al. (2014)).Last Full time schooling, perhaps by favouring concentration, has positive effects on the acquisition of CS.

1.5.2 DiD-SFA for assessing the impact of educational programs on students NCS

DiD-SFA were calculated with respect to NCS 2015 and 2018 (Table 9, where only variables significant at least at 10% are retained). DiD-SFA does not suffer from endogeneity problems, because, first, covariates are limited to student characteristics unaffected by the inefficiency of schools. Second, inputs include NCS and some student characteristics, such as gender and socioeconomic status measured in 2015: while INVALSI Italian and INVALSI Maths outputs are measured in 2018. Therefore, inputs cannot be endogenous with respect to outputs measured afterwards.

The assumptions of the DiD model held, as follows: first, SUTVA: in the dataset, either all classes in the same school carried out the educational programme to increase NCS or none did; second, EXOG: the covariates in the model are student INVALSI 2015 collected before the treatment, social capital, the socioeconomic and demographic characteristics of students, uninfluenced by the treatment; third, NEPT: educational programmes were implemented between the 5th and 8th grades; fourth, CT: covariates X are time-invariant; fifth, COSU: each student has a positive probability of receiving treatment. All the assumptions hold. Therefore, ATET1 is identified and DiD-SFA estimates the causal effect of educational programmes on student NCS.

On the basis of the results, the various NCS dimensions can be classified into three groups. The first group comprises NCS whose DiD-SFA shows significant differences between treated and non-treated classes. These are the NCS most closely related to student personalities: Optimism, Relational stability and Emotional stability. The second group comprises NCS which do not show a significant difference between treated and non-treated classes, but Gamma relative weights (which show the importance of time-invariant stochastic inefficiency) are significant. This group includes: Relational stability, Learning orientation and Motivation. The third group comprises NCS with no significant differences between treated and non-treated classes and Gamma relative weights that are almost zero. This group includes Self-Efficacy, Performance Orientation and Inner Stability. As regards the covariates, INVALSI Italian and Maths 2015 are significant only for emotional stability. Of the social capital variables, computer use, reading a book, doing homework, challenge education, often have positive and significant parameters. They express a positive attitude to reality and, therefore, have a positive impact on some NCS, whereas watching television often has a negative significant sign because it expresses a propensity to waste time. Playing with friends, helping at home, playing sports, music, theatre, language courses, have positive and negative signs, depending on the different nature of NCS. Finally, socioeconomic conditions, nationality and the decision to continue personal studies at classical or scientific high schools, have the expected positive impacts on NCS.

1.6 Conclusions

Our paper belongs to the broader literature that jointly analyses efficiency and effectiveness following a wholistic approach and proposes to include NCS in the analysis as specific contribution to the research in this area. We follow two approaches. The first approach, called “static NCS efficiency”, is based on a SFA where initial CS, NCS and other control variables are the inputs, while final CS are the outputs. The second approach defined “dynamic NCS efficiency” is based on an SFA-DiD and measures the increase in students NCS given their participation in educational programmes.

Our analysis can be improved and extended if more appropriate measures of NCS variables will be available. In Italy, there is already an ongoing debate on how to measure students NCS. Recently, it has been decided to introduce a portfolio for students at the last year of high school, which collects their NCS characteristics; however, the definition of NCS is still more a qualitative list and not yet a quantitative evaluation.

NCS efficiency may be further implemented if one takes into account also other aspects, traditionally considered in efficiency studies, such as financial and non-financial resources of schools (facilities, buildings, laboratories), technical, organizational and managerial characteristics of principals and teachers, school environment, student/teacher ratio (Lockheed & Hanushek (1994); De Witte & López-Torres (2017); Masci et al. (2018)). Furthermore, NCS Efficiency could be integrated with information regarding teacher characteristics and their capacity to enhance NCS (Hanushek & Rivkin (2010); Chetty et al. (2014); Kim et al. (2018); Kraft (2019); Agasisti et al. (2018)). Moreover, by collecting panel data regarding students from the beginning of primary school until the end of high school, longitudinal NCS Efficiency in the entire school system could be studied (Fondazione Agnelli (2018); AlmaLaurea (2019); OECD (2019)).

The development of NCS efficiency, however, also depends on the use of more sophisticated statistics techniques. As in Colombi et al.(Colombi et al. (2014)), it is possible to break inefficiency down into four parts: 1) time-invariant (long-run) inefficiency due to some factors that cannot be changed in a school's organization (buildings, laboratories); 2) the entire production process or, at the family level, wealth, not changeable in the short term; time-varying (short-run) inefficiency, due to more likely time varying inputs, such as annual personnel budget, educational programmes, teaching methods; 3) specific inefficiencies, i.e. the latent heterogeneity of schools or classes generated by factors not described by observed covariates; 4) random disturbances.

This decomposition of inefficiency into four terms would enhance understanding of the difficulties in transforming NCS into CS. If inefficiency in transforming NCS into CS depends on time-invariant inefficiency linked to permanent organisations and school characteristics, long-term investments are necessary to change what schools can offer in educational terms. On the other hand, if inefficiency is related to time-variant factors, the review of policy could be quicker. If inefficiency is due to non-observed factors, these factors need to be investigated and identified in order to improve education.

NCS efficiency approach is not an end in itself, but a possible new tool for future educational policy interventions aimed at improving NCS of young people, as the experience of PAT shows. The results call for a reflection on the importance of the introduction of educational methods more learning-oriented, aimed at fostering creativity and engagement of students in class and in their educational pathways.

Appendix

Institutional background: the experience of PAT

The present research project has been supported, promoted and funded by the Provincia Autonoma di Trento (PAT, the Trento Autonomous Provincial Authority) through the ongoing work of IPRASE, the local institution devoted to research on education and schooling. Indeed, it is the first case in Italy of empirical research targeting schools and students, developed and supported by local educational institutions. The support of local institutions has been especially important in sponsoring the research among head teachers, directors, teachers, and parents, in the Trento area. This initiative has involved a large number of schools and students, with a keen interest in our project and with the active participation of teachers. Teachers' participation was particularly important to classify existing educational activities for NCS and to develop appropriate new school treatments. Furthermore, Provincia Autonoma di Trento has provided the research group with access to administrative data.

Figures

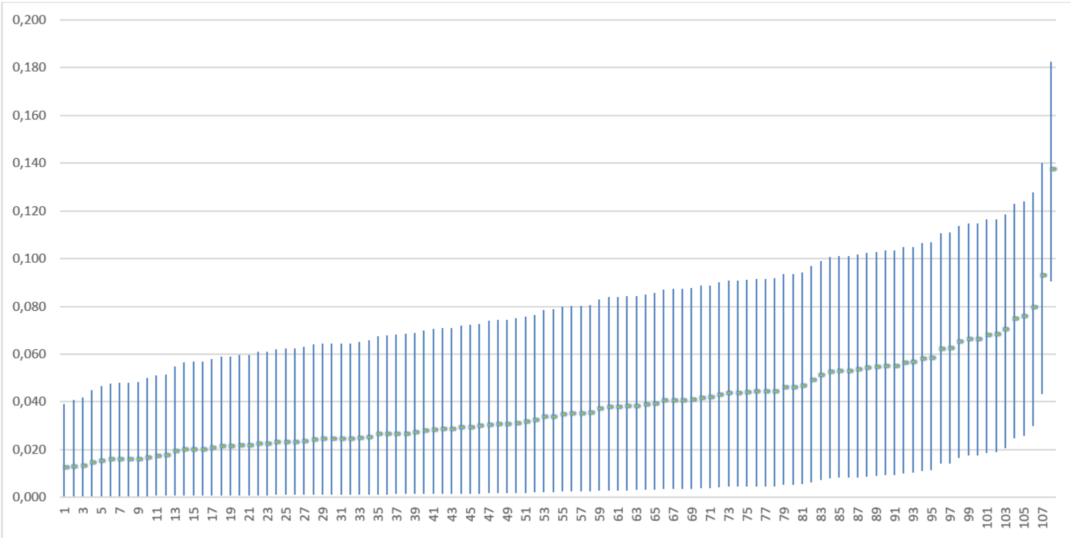

Figure 1.1: Inefficiency coefficients Italian

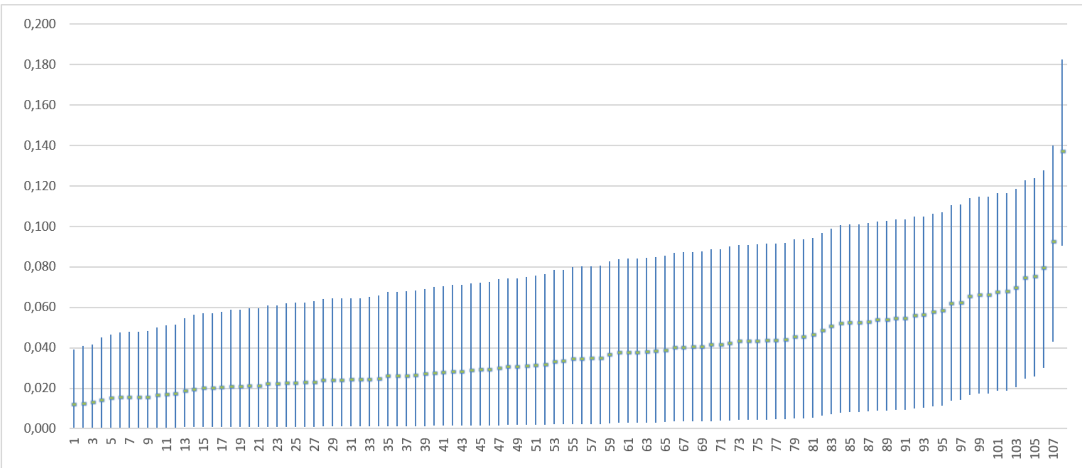

Figure 1.2: Inefficiency coefficients Math

Tables

Table 1.1: T-test mean(x) - mean(y) INVALSI Italian 2018

Group	Obs	Mean	Std Dev
x	52	208.4684	7.1991
y	25	210.5079	6.6226
x-y		-2.0395	
t(x)-t(y)		-1.229	
d. of freedom		54.7	
$\Pr(\lvert T\rvert > \lvert t\rvert)$		0.11053	

Table 1.2: T-test mean(x) - mean(y) INVALSI Maths 2018

Group	Obs	Mean	Std Dev
x	52	214.791	8.6055
y	25	217.1776	7.5085
x-y		-2.3686	14.942
t(x)-t(y)		1.244	
d. of freedom		60.2	
$\Pr(\lvert T\rvert > \lvert t\rvert)$		0.11041	

Table 1.3: Comparison between INVALSI 2015 and PAT 2018 NCS

INVALSI 2015	PAT 2018 NCS
Well-being at school 2015	Optimism
Italian self-concept, Math self-concept	Self-efficacy
Quality of class relations 2015	Relational stability
Learning oriented	Learning oriented
Motivation 2015	Motivation
Performance oriented 2015	Performance oriented
Anxiety during INVALSI test 2015	Emotional stability
Bullying acted 2015, Bullying suffered 2015	Inner stability

Table 1.4: Variables

CS 2018 dependent variables	External support for studying 2015
INVALSI score Italian 2018	Well-being at school 2015
INVALSI score Maths 2018	Performance oriented 2015
Covariates	Learning oriented 2015
CS 2015	**Social Capital variables**
INVALSI score Italian 2015	Watching television, DVD
INVALSI score Maths 2015	Using computer, videogames
NCS 2018	Playing with friends
Inner stability	Helping at home
Relational stability	Reading a book
Emotional stability	Doing homework
Self-efficacy	Playing sports
Motivation	Music, theater, languages courses
Optimism	Challenge education
Performance oriented	Management education
Learning oriented	ESCS 2018
NCS 2015	**Control variables**
Bullying acted 2015	Male
Bullying suffered 2015	Italian parent
Class relations 2015	High school
Anxiety during INVALSI test 2015	Kindergarten
Italian self concept 2015	Full time vs Part time
Math self concept 2015	Adige Valley
Motivation 2015	

Table 1.5: Descriptive statistics

	count	mean	sd	min	max
IDSCUOLA	108	27.54	15.35	2	58
INVALSI 2018 Italian	108	210.4	11.39	182.8	259.7
INVALSI 2018 Maths	108	217.1	12.37	191.3	273.4
INVALSI 2015 Italian	108	206.9	13.03	175.5	242.0
INVALSI 2015 Maths	108	213.6	13.00	189.8	259.2
Inner stability	108	0.0456	0.188	-0.522	0.990
Relational stability	108	0.0138	0.229	-0.569	0.491
Emotional stability	108	-0.0288	0.279	-0.784	0.660
Self-efficacy	108	0.0396	0.159	-0.426	0.690
Motivation	108	-0.0794	0.380	-0.990	1.293
Optimism	108	0.0413	0.220	-0.495	0.950
Performance oriented	108	0.00434	0.221	-0.504	0.704
Learning oriented 2015	108	0.00291	0.110	-0.231	0.615
Bullying acted 2015	108	0.000244	0.128	-0.270	0.427
Bullying suffered 2015	108	-0.00154	0.183	-0.360	0.614
Class relations 2015	108	0.00750	0.171	-0.474	0.660
Anxiety 2015	108	0.00312	0.207	-0.623	0.476
Italian self-concept 2015	108	0.00800	0.199	-0.318	0.900
Math self-concept 2015	108	0.00786	0.224	-0.517	0.818
Motivation 2015	108	-0.339	0.451	-1.300	1.164
Support for studying 2015	108	0.00141	0.163	-0.268	0.581
Well-being 2015	108	0.00796	0.167	-0.438	0.510
Performance oriented 2015	108	0.00682	0.224	-0.425	0.671
Learning oriented	108	0.0263	0.160	-0.391	0.372
Watching television, DVD	108	2.810	0.280	2.143	3.500
Using computer, videogames	108	2.110	0.332	1	3.077
Playing with friends	108	3.325	0.328	2.571	3.941
Helping at home	108	2.493	0.280	1.786	3.231
Reading a book	108	1.891	0.379	1.231	4
Doing homework	108	2.983	0.307	2.211	4
Playing sports	108	2.598	0.350	1.833	3.615
Music, theater, languages courses	108	1.536	0.291	1	3
Challenge	108	0.0142	0.223	-0.575	0.501
Management	108	0.0111	0.338	-0.956	0.697
ESCS 2018	108	0.160	0.364	-0.851	1.961
Male	108	0.494	0.128	0	0.833
Italian parent	108	0.892	0.114	0.385	1
Adige Valley	108	0.343	0.477	0	1
High School	108	0.486	0.186	0.133	1
Full time	108	0.797	0.318	0	1
Kindergarten	108	0.880	0.257	0	1

Table 1.6: SFA Italian and maths

VARIABLES	INVALSI 2018 Italian	INVALSI 2018 Maths
Inner stability	13.281***	34.722***
	(4.162)	(6.600)
Emotional stability	7.162***	8.369**
	(2.452)	(3.423)
Optimism		16.334***
		(5.333)
Anxiety 2015	-11.316***	
	(3.435)	
INVALSI 2015 Italian	0.403***	
	(0.055)	
INVALSI 2015 Maths		0.244***
		(0.070)
Learning orientation 2015		30.693***
		(8.870)
Performance orientation 2015		9.580**
		(4.260)
Italian self-concept 2015		14.506***
		(4.948)
Doing homework	5.850**	
	(2.283)	
ESCS2018	6.355***	5.775**
	(2.051)	(2.866)
Italian parent		19.952**
		(8.598)
Full time		8.687***
		(3.014)
Kindergarten	7.756***	10.515***
	(2.606)	(3.533)
Constant	101.544***	129.542***
	(16.093)	(29.022)
Usigma	-3.308***	-3.281***
	(-120.173)	(-298.162)
Vsigma	3.777***	4.327***
	(0.141)	(0.147)
Gamma	0.275	0.435
Observations	108	108

Table 1.7: Inefficiency coefficients - Italian

	Less efficient					Most efficient				
	N	mean	sd	min	max	N	mean	sd	min	max
INVALSI 2015 Italian	11	207.5	18.22	175.5	242.0	11	212.6	9.902	196.9	228.3
INVALSI 2015 Maths	11	216.5	16.63	197.9	259.2	11	216.1	14.37	194.7	246.6
ESCS 2018	11	0.0354	0.390	-0.497	0.905	11	0.0925	0.343	-0.851	0.391
Male	11	0.484	0.166	0.250	0.833	11	0.463	0.0995	0.333	0.643
Full time	11	0.841	0.257	0.118	1	11	0.701	0.388	0	1
Adige valley	11	0.273	0.467	0	1	11	0.273	0.467	0	1
Kindergarten	11	0.839	0.296	0	1	11	0.818	0.328	0	1
High school	11	0.482	0.126	0.267	0.667	11	0.530	0.229	0.214	1
Italian parent	11	0.856	0.138	0.667	1	11	0.917	0.0839	0.727	1

Table 1.8: Inefficiency coefficients - Maths

	Less efficient					Most efficient				
	N	mean	sd	min	max	N	mean	sd	min	max
INVALSI 2015 Italian	11	213.2	10.75	199.0	229.9	11	211.5	11.67	193.4	228.3
INVALSI 2015 Maths	11	221.9	10.74	204.8	244.0	11	217.9	13.98	194.7	246.6
ESCS 2018	11	0.385	0.657	-0.306	1.961	11	0.228	0.171	0.00773	0.598
Male	11	0.464	0.214	0	0.833	11	0.487	0.124	0.286	0.643
Full time	11	0.806	0.358	0	1	11	0.784	0.333	0.143	1
Adige valley	11	0.636	0.505	0	1	11	0.545	0.522	0	1
Kindergarten	11	0.851	0.304	0	1	11	0.830	0.334	0	1
High school	11	0.564	0.225	0.300	1	11	0.509	0.132	0.214	0.667
Italian parent	11	0.914	0.0905	0.750	1	11	0.921	0.0501	0.857	1

Table 1.9: SFA DiD

	Optimism	Self-efficacy	Relational stability	Learning orientation
Treated	0.097***		0.085**	
	(0.031)		(0.043)	
Challenge	0.260***			0.150***
	(0.092)			(0.049)
INVALSI 2015 Italian				
INVALSI 2015 Maths				
Watching televion, DVD				
Using computer	0.089***			0.059**
	(0.032)			(0.028)
Playing with friends		-0.041*	0.105**	-0.046**
		(0.021)	(0.047)	(0.019)
Helping at home				0.048*
				(0.027)
Reading a book	0.075**	0.101*	0.064***	
	(0.035)	(0.052)	(0.019)	
Doing homework				0.078***
				(0.015)
Playing sports			-0.067***	
			(0.026)	
Music, theater,..				-0.061***
				(0.019)
Italian parent	0.167***		0.352***	
	(0.057)		(0.072)	
ESCS 2018	0.108***			
	(0.037)			
High school	0.189***		0.156***	0.184***
	(0.047)		(0.040)	(0.063)
Kindergarten	-0.172*	-0.242***		0.091**
	(0.095)	(0.072)		(0.039)
Full time		-0.059**	-0.103***	
		(0.029)	(0.027)	
Adige valley	-0.048***			
	(0.019)			
Constant			-0.749***	
			(0.222)	
Usigma	-10.752***	-10.860***	-4.974***	-5.823***
	(1.005)	(0.251)	(0.769)	(0.692)
Vsigma	-3.674***	-3.865***	-3.665***	-4.471***
	(0.097)	(0.071)	(0.282)	(0.204)
Gamma	0.001	0.001	0.196	0.205
Observations	204	204	204	204

	Motivation	Performance orientation	Emotional stability	Inner stability
Treated			-0.212***	
			(0.045)	
Challenge			-0.203**	
			(0.101)	
INVALSI 2015 Italian			0.004***	
			(0.001)	
INVALSI 2015 Maths			0.004***	
			(0.001)	
Watching television, DVD	-0.231**		0.130***	
	(0.096)		(0.040)	
Using computer			-0.102***	
			(0.037)	
Playing with friends		-0.170***		-0.073***
		(0.053)		(0.017)
Helping at home		-0.083**		0.053**
		(0.040)		(0.022)
Reading a book				0.080***
				(0.026)
Doing homework	0.250***			0.072***
	(0.057)			(0.026)
Playing sports			-0.095**	
			(0.048)	
Music, theater			0.105***	0.060*
			(0.041)	(0.032)
Italian parent				
ESCS 2018				
High school	0.311**		-0.207*	0.089**
	(0.153)		(0.106)	(0.041)
Kindergarten				-0.149**
				(0.070)
Full time		-0.099*		-0.056*
		(0.053)		(0.029)
Adige valley		0.078**		-0.037***
		(0.039)		(0.014)
Constant		1.794***		
		(0.274)		
Usigma	-4.699***	-10.273***	-5.579**	-10.983***
	-1.580	(0.224)	-2.696	(0.449)
Vsigma	-2.868***	-3.205***	-3.155***	-3.910***
	(0.281)	(0.056)	(0.253)	(0.079)
Gamma .	0.138	0.001	0.081	0.001
Observations	204	204	204	204

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2. THE IMPACT OF INFORMAL AND FORMAL CARE DISRUPTION ON OLDER ADULTS' PSYCHOLOGICAL DISTRESS DURING THE COVID-19 PANDEMIC IN UK

Abstract

This paper exploits individual-level data from the U.K. Household Longitudinal Study (U.K.HLS), Understanding Society, to investigate how formal and informal caregiving disruptions—due to the U.K. government's non-pharmaceutical interventions (NPIs) aimed at reducing transmission of the SARS-CoV-2 virus—may have affected the likelihood of psychological distress among older individuals. We model the association between disruption of formal and informal care and mental health of the elderly during the first wave of the COVID-19 pandemic using a recursive simultaneous- equation model for binary variables. Our findings reveal that public interventions, which are most essential for reducing the pandemic spread, influenced the provision of formal and informal care. The lack of adequate long-term care following the COVID-19 outbreak has also had negative repercussions on the psychological well-being of these adults.

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2.1 Introduction

The first national lockdown to mitigate the transmission of COVID-19 in the U.K. was introduced on March 23, 2020 and remained in place until July 4, 2020. During the lockdown the government imposed national restrictions and required all those who could to work from home, closed all but essential shops, and advised the population to stay at home and limit contact with other people outside of their households. Moreover, the U.K.'s National Health Service (NHS) identified specific "clinically vulnerable" individuals thought to be at higher risk of severe COVID-19 complications and related deaths, and strongly advised them to stay home and avoid all face-to-face contact. The entire elderly population, regardless of individual medical conditions, was also considered clinically vulnerable and advised to stay home as much as possible (UK (2020); Cabinet Office (2020)).

Although effective in preventing a further dissemination of COVID-19, these interventions were immensely disruptive to people's social connections and had potential repercussions on sectors with high direct face-to-face contact—e.g., the healthcare industry and social services (Bu et al. (2020)). Vulnerable groups such as older people encountered unique and remarkable challenges in coping with their care needs without leaving their homes (CarersUK (2020)).

In the U.K., elderly support is dependent upon a combination of informal and formal care: statutory-source community care and social services, privately paid care workers, neighbours, friends, and family members (Vlachantoni et al. (2015); Maplethorpe et al. (2015)). The strict restrictions introduced by the U.K. government, together with the reorganization of the healthcare system at all levels, produced a disruption in both types of caregiver activities (Topriceanu et al. (2021)).

Previous literature on the effects of the COVID-19 pandemic on long-term care (LTC) has paid significant attention to the limited availability of formal care services during the pandemic. For example, social distancing and competing care needs within households due to school closures may have placed additional burdens on family caregivers in terms of objective (i.e., hours spent on caring) and subjective burdens (i.e., mental health and quality of life) (see, for instance, Maccora et al. (2020); Rodrigues et al. (2021); Tsapanou et al. (2021); Leggett et al. (2021); Monteiro et al. (2022); McGarrigle et al. (2022);

Costi et al. (2023)). However, an investigation into the effects of COVID-19 and its accompanying control measures on formal and informal care disruptions, on elderly unmet care needs, and health-related outcomes (i.e., physical, and mental health) has remained relatively scant.

Relying on data from the Understanding Society COVID-19 Survey (April 2020) during first the COVID-19 wave across the U.K, Evandrou et al. (2020) provided the first descriptive evidence on informal care disruptions affecting the elderly during this time. The authors investigated the extent of support received by older people from family, friends, and neighbours in the first period of the lockdown. According to their findings, a significant proportion of older people received an increased level of help (ranging from shopping, dressing, meal preparation, assisting with online or internet access, gardening, or house repairs) from those who had provided care to them before the outbreak or from new caregivers. This was especially the case among those living alone or with a partner aged 70 and over. However, Evandrou et al. (2020) also showed that a smaller group of frail elderly people with difficulties in performing key activities of daily living suffered from an informal care disruption and received less care and support during the lockdown compared to the pre-COVID-19 outbreak period. This evidence raised the spectre that a group of older vulnerable individuals might not have received an adequate level of social care during the lockdown.

Tur-Sinai et al. (2021) investigated how the initial outbreak influenced the supply of formal and informal care among the elderly in need in 23 European countries and Israel by using data from the Survey of Health, Ageing and Retirement in Europe (SHARE Corona Survey), again adopting a descriptive approach. According to their findings, in the first months of the outbreak, informal care appeared to be more resilient than formal care services; indeed, a significant proportion of older adults in European countries continued to receive informal help, enjoying an increase in the amount of care from children, neighbours, friends, and colleagues, while informal help from other relatives decreased. Alternatively, older adults encountered great difficulty in obtaining formal help from professional caregivers.

Brugiavini et al. (2022) investigated whether the disruption of elderly parent–adult child contacts due to social distancing restrictions, which characterized European countries during the first wave of the pandemic, increased symptoms of depression in the elderly, using the eighth wave of the SHARE and the SHARE Corona Survey. They adopted a joint model of parent-child contact disruption and mental health issues, estimated by using a recursive bivariate probit model. Their findings showed that interventions deemed essential to reduce the spread of the pandemic, including physical distancing and other epidemiological control measures (e.g., stay-at-home orders, travel restrictions, and so forth), disrupted some personal parent–child contacts, with negative consequences on the elderly parents' mental health.

To the best of our knowledge, no studies have been conducted on the connection between disruption of formal care and its potential impact on the elderly population's mental health, nor on the inter-relationship between formal and informal care disruptions due to lockdown restrictions and older adults' mental-health deterioration in the U.K context. This paper aims to fill this gap by providing additional insights regarding the short-term consequences of mental health care disruptions to the elderly during the COVID-19 outbreak on the elderly The empirical evidence provided by this paper may shed light on the importance of designing public policies to contain pandemic crises with the realization that some population groups are more affected than others. Hence, these groups need different social restrictions from those imposed on the general population since they may suffer more from the consequences of isolation and reduction in social contacts (Gulland (2020); CarersUK (2020)).

For the purposes of our study, we used data from the U.K. Household Longitudinal Study (U.K.HLS) Understanding Society (waves #9 and #10), and the COVID-19 Survey (wave #1, April 2020). Following Brugiavini et al. (2022), we attempt to study the complex relationship between informal and formal care disruption and elderly psychological well-being. As such, we used a simultaneous equation model for binary variables: Specifically, we constructed a joint model of informal care and formal care disruption and mental health conditions that considers an individual's unobserved heterogeneity that may characterize this relationship.

Our findings show that the disruption of informal and formal support represents a significant risk factor for psychological well-being in older adults and increases their risk of depression.

2.2 Data

This study uses individual-level data from the U.K. Household Longitudinal Study (U.K. HLS), Understanding Society, a nationally representative panel study of the British population. For the HLS, sample members living in the U.K. were interviewed annually since 2009 with the aim of recruiting over 100,000 individuals in 40,000 households. The first wave of the study and data collection period spanned two years and thus wave #1 ran from 2009 to 2011, wave #2 from 2010 to 2012, and so on. Since April 2020, a subsample of participants from the U.K. HLS survey have been interviewed each month, and they completed short web surveys that focused on the impact of the COVID-19 pandemic. The short web surveys covered the changing impact of the pandemic on the welfare of individuals and households. Each month, participants completed one survey that included core content designed to track changes alongside variable updated content as the coronavirus situation developed. Core modules included detailed information on household composition, coronavirus illness, long-term health conditions management, mental health measures, loneliness, and employment. Individuals were identified by a personal unique identifier that remained for all waves and could be used to link respondents' information across different waves (Institute for Social and Economic Research (2020*a*)).

The integrated data set used for this analysis is the result of matching wave #9 (2017-2019) and #10 (2018–2020) of the main survey and the first month of the COVID-19 wave (April 2020). This data set provided us the opportunity of gathering information related to the COVID-19 outbreak and the years before it.

After correcting for missing values, the sample included 3,721 individuals. In this paper, we focused specifically on individuals aged 65 and over and found that the COVID-19 pandemic took a heavy toll on their physical as well as mental health. The measures adopted by the U.K. government regarding social distancing and isolation to protect the elderly from risk of infection often resulted in social isolation and loneliness (to which older adults are more vulnerable because of their functional dependency) that in turn might have increased their likelihood of depression (Banerjee (2020)).

2.3 Empirical Strategy

2.3.1 Dependent variables

As previously discussed, the main aim of this study was to investigate the potential effects of informal and formal care disruptions on the mental health deterioration of older people in the U.K during lockdown restrictions intended to curb the COVID-19 spread.

The first step toward a full understanding of this effect required a complex model that considered the simultaneous relationships between informal and formal care disruption and older individuals' psychological well-being. Following Brugiavini et al. (2022), we employed a simultaneous equation model for binary variables. We constructed a joint model of informal and formal care disruption and mental health outcomes that we estimated through a recursive multivariate probit model that considers individuals' unobserved heterogeneity that may characterize these relationships (see Subsection 2.3.2). A recursive model is a special case of a system of equations in which the endogenous variables are determined in sequence. Thus, the right-hand side of the reduced-form equations for the endogenous variables include exogenous variables only. The right-hand side of the structural equation includes the exogenous variables and the endogenous variables estimated by the reduced-form equations. The model's development may be traced back to the pioneering work of Heckman (1978), and it is a common approach to deal with the endogeneity of binary dependent variables.

Thus, we identified two classes of dependent variables: informal and formal care reception and mental health outcomes—i.e., older individuals' psychological distress. To measure individuals' psychological distress, we used the 12-item Generalised Health Questionnaire (GHQ-12), which is one of the most widely used screening tools for psychological distress that has been validated for epidemiological studies (Goldberg et al. (1997)). The GHQ-12 was collected in all waves of the U.K. HLS Understanding Society to date and included in the Understanding Society COVID-19 Survey. Each one of its 12 items regarding symptoms, feelings, or behaviours is answered on a four-category Likert scale ranging from "not at all" to "much more than usual": categories 1 and 2 ("not at all," "no more than usual") were scored as 0, and categories 3 and 4 ("rather more than usual," and "much more than usual") were scored as 1 [1]. Finally, the scores from the 12 items

[1]The GHQ-12 items refer to difficulties with sleep, concentration, problems in decision making, feeling

were added to obtain an overall score. The measure attained in this way is called GHQ-12 Caseness and respondents scoring 3 or more (out of a possible total of 12) are likely to be experiencing anxiety and/or depression (Cox et al. (1987)). In line with the literature, GHQ-12 Caseness > =3 is used as the threshold to define our dichotomous outcome variable (Lindkvist & Feldman (2016); Aalto et al. (2012); Holi et al. (2003)) [2].

To generate a variable that accurately measures the disruption of informal care, we considered the following questions included in the first wave of the Understanding Society COVID-19 Survey: "Thinking about the last 4 weeks, did you receive support from family, neighbours or friends who do not currently live in the same house/flat as you?" (with "yes" or "no" answer options), and "Thinking back to earlier this year, before the outbreak of the coronavirus pandemic. How has the help and support you receive from family, friends or neighbours who do not live in the same house/flat as you changed?" (Response options included: "1. There has been no change; 2. I receive more help from some people who previously helped me; 3. I receive less help from some people who previously helped me; 4. I currently receive help from family, friends or neighbours who did not previously help me"). To capture a potential disruption in informal care, we constructed a binary variable that takes the value of 1 if respondents reported they had not received informal care in the last 4 weeks before the interview (from non-cohabiting family members, neighbours, or friends), but they had received help before the outbreak, or if they had received less help from certain people who previously helped them, and 0 otherwise (if they had received support in the last 4 weeks before the interview, or if they had not received support in the last 4 weeks before the interview, but there has been no change with respect to the pre-outbreak period).

In reference to formal care (i.e., community health and social care services), the Understanding Society COVID-19 Survey asked respondents "in need" of formal care to report whether they had received help with personal care/ medications/ shopping/ cooking/ cleaning/ wound dressing/ injections from someone visiting them at home regularly before the pandemic restrictions [3]. The answers ranged from 1 to 4, specifically: "1. Yes,

overwhelmed, and other indicators of distress.

[2]As a sensitivity check we also re-ran the model with a different threshold identifying mental health conditions at (do you mean "using"?) four symptoms. Results confirm those of the main analysis (see the Appendix).

[3]In this question, "in need" meant those who had reported at least one health condition (i.e., asthma, arthritis, congestive heart failure, coronary heart disease, angina, heart attack or myocardial infarc-

as before; 2. Yes, but with reduced support; 3. Yes, with increased support; 4. No." We constructed a binary indicator that takes a value 1 if respondents, who needed formal care, reported they had experienced a reduction in community health and social care services in 2020, or they did not receive any services compared to the pre-pandemic period, and 0 otherwise.

According to Evandrou et al., (2020) a relatively low proportion of the elderly reported a disruption in informal care and formal care received during the first COVID-19 wave. Indeed, about 4% of the elderly in our sample experienced a disruption in informal care received, while about 3% reported a disruption in formal care.

2.3.2 Estimation method

Identifying an association between formal and informal care disruption and the mental health of the elderly may be complicated by the presence of endogeneity. Older individuals' isolation, resulting from the U.K. government restrictions to contain the virus, might have increased the risk of depression while simultaneously influencing access to formal and informal support (Cacioppo et al. (2006); Holt-Lunstad et al. (2010)). In this application, the situation is further complicated because both formal and informal home care may be simultaneously determined (Van Houtven & Norton (2004)). Indeed, receiving informal care may be correlated to unobserved health characteristics or to unobserved preferences for care that are likely to influence the demand for formal care (Charles & Sevak (2005); Bonsang (2009)). Moreover, the probability of accessing formal care and informal care may have been influenced by the pandemic. As such, we estimated the model using a recursive multivariate probit design. The recursive structure of the multivariate probit model builds on a structural-form equation that determines the probability of the onset mental health conditions and two reduced-form equations: one for the potentially endogenous dummy variable measuring the disruption of informal care received; and the other for the potentially endogenous dummy variable measuring the disruption of formal care.

Hence, we identified two classes of dependent variables: care disruption—namely,

tion, stroke, emphysema, chronic bronchitis, chronic obstructive pulmonary disease, cystic fibrosis, hypothyroidism or an under-active thyroid, cancer, diabetes, epilepsy, high blood pressure/hypertension, emotional, nervous or psychiatric problem, multiple sclerosis, H.I.V., chronic kidney disease, conditions affecting the brain and nerves, motor neurone disease, learning disability or cerebral palsy, problems with spleen, obesity, other long standing/chronic condition), or were having/waiting for treatment at the time of the interview (such as an operation or procedure planned, targeted therapy, tests/consultations).

formal, and informal care—and health outcome (i.e., the dummy indicator for individuals' mental health as measured by the GHQ-12 Caseness score). In the structural equation for mental health, formal and informal care disruption are included as regressors.

We constructed and estimated a system of three equations with two reduced-form equations and one structural equation represented by the mental health equation. Thus:

$$\begin{aligned} {}^{*}_{3i} &= \beta_3' x_{3i} + \epsilon_{3i} = \delta_1 y_{2i} + \delta_2 y_{3i} + \alpha_3' z_{3i} + \epsilon_{3i} \\ y^{*}_{2i} &= \beta_2' x_{2i} + \epsilon_{2i} \\ y^{*}_{1i} &= \beta_3' x_{1i} + \epsilon_{1i} \end{aligned} \tag{2.1}$$

where x_{li} (with $l = 1, 2$) and z_{3i} are vectors of exogenous variables, β_2, β_3 and α_3 are parameter vectors, and δ_o (with $o = 1, 2$) are scalar parameters. The error terms distributed as multivariate normal are ϵ_{hi}(with $h = 1, 2, 3$), each with a mean zero, and variance covariance matrix Σ. Σ has values of 1 on the leading diagonal and correlations $\rho_{jk} = \rho_{kji}$ on the off-diagonal elements (where ρ_{jk} is the covariance between the error terms of equation j and k).

In the abovementioned setting, the exogeneity condition is stated in terms of the correlation coefficients, which can be interpreted as the correlation between the unobservable explanatory variables of the different equations. All equations in system (2.1) can be estimated separately as single probit models only in the case of independent error terms (i.e., the coefficient ρ_{jk} is not significantly different from zero).

Conventionally, the identification of a recursive multivariate probit model has been based on exclusion restrictions to obtain a more robust identification of the parameters. Maddala (1983) proposed that at least one of exogenous variables (i.e., in the vectors x_{1i} and x_{2i}) of the reduced-form equations is not included in the structural equation as an explanatory variable. However, more recent work by Wilde (2000) shows that identification is achieved even if the same regressors appear in all equations providing there is sufficient variation in the data (i.e., providing each equation contains at least one varying exogenous regressor). However, this result is valid in the context of multivariate normal distribution, and, in the absence of additional instruments, identification strongly relies on functional form—i.e., normality of the stochastic disturbances, commonly referred to as identification by functional form (Li et al. (2021)). It is therefore common practice to impose exclusion restrictions to improve identification of the causal parameters δ_1 and

δ_2. These exclusion restrictions (instruments) should be causally linked to informal and formal care disruption and should affect individuals' mental health only through their effects on informal and formal care disruptions. The instruments are discussed in detail in Subsection 2.3.3.

2.3.3 Exclusion restrictions

This subsection describes the exclusion restrictions that we adopted for both reduced-form equations.

- *Disruption of informal care equation*

  The emergence of COVID-19 and the measures implemented by the U.K. government to curb its spread forced frail older people indoors and reduced opportunities to remain socially connected. In March 2020, a stay-at-home order was issued that banned all non-essential movements and contact with other people outside the household. This restriction had important repercussions on the continuity of the informal care provision mainly because (non-cohabiting) caregivers faced difficulties traveling to the homes of recipients. In a period characterized by stringent mobility restrictions, traveling a small geographical distance to provide help might have represented an important barrier to caregiving. Wave #9 of the Understanding Society Survey includes a question regarding which non-coresident relatives' respondents are "alive at the moment." Respondents with children living outside the household were then asked how long it takes them—door to door—to travel to their sons' or daughters' residences (aged 16 or over). If respondents reported they have more than one non-coresident child aged 16 or over, they were asked to think about the child with whom they have the most contact. Thus, we create a binary variable that takes the value of 1 if respondents lived more than 30 minutes travel time from their children (time taken by usual mode of transport) and 0 otherwise (the cut-off was chosen following Li et al. (2021); Thomas & Dommermuth (2020); Artamonova & Syse (2021)). In the first U.K. lockdown, which started on 23 March 2020, people were advised to stay home and to leave their home for essential reasons only, such as to attend essential work, acquire food or medicine, go to the hospital, exercise once a day, or provide care or assistance to a vulnerable person. Travel restrictions prevented people from travelling outside their local area, namely their village, their town, or a part of the city where they live with no specific indications of "travel distance". So, in choosing the cut-off we followed the previous literature wherein a travel time of approximately 30 minutes can be considered a "short distance"—i.e., in principle, this allows frequent contact and supports exchanges between caregivers and receivers. Hence, geographical proximity was measured as a dummy variable: long distance (more than 30 minutes' travel time) against short distance (less than 30 minutes' travel time). We combined adult child caregivers who live less than 15 minutes away with those who live 15–30 minutes away (see Li et al. (2021); Thomas & Dommermuth (2020); Artamonova & Syse (2021)). Among the control variables, we did not consider co-residing children, since the questions related to informal care refer to care and support received from family, neighbors, or friends who do not currently live in the same house/flat as the respondent. We also include in the reduced-form equation for informal care disruption a binary variable that takes the value of 1 if none of the respondent's friends live in his or her local area. We gathered this information from wave #9 in the "Family Networks" and "Social Network" modules, respectively (that were not included in the most recent waves #10 and the COVID-19 Survey), by assuming that non-proximity with children and friends remained broadly constant over time.

- *Disruption of formal care equation*

  While the U.K.'s NHS provides universal healthcare, the provision of publicly funded formal long-term care (LTC) services is based on a needs assessment (i.e., whether the potential care recipient can eat, wash, or dress without help) and means assessment (i.e., income that includes pensions, benefits, and assets), and it is a statutory responsibility of local authorities. In cases where care needs do not meet the criteria or financial means are above the threshold, formal care services should be privately purchased: individuals being cared for (or their family) pay all or most of the costs for their care. In the last decade, the means test has become meaner, and the usage rate of social services has declined. Among those who must pay for themselves, cost was often cited as a reason for not seeking help (AgeUK (2022)). The pandemic further exacerbated this affordability challenge for many older households, and thereby increased their risk of care disruption (Phillipson et al. (2021)). The Social Care Module of the wave #9 of the Understanding Society Survey includes information about who usually manages payment for the care provider. We created a binary variable that takes the value of 1 if the respondents themselves paid for all formal pre-pandemic care services without any support from family, friends, or local authorities. We expect that those who did not receive any support in paying for the costs of services might have significantly suffered from worse care access and a higher probability of formal care disruption.

2.3.4 Other independent variables

Table 2.1 shows the other independent variables in the three equations model of (2.1), grouped into listed categories.

For our study, we considered the following categories: demographics, socioeconomic variables, and health conditions that existed before the COVID-19 outbreak. Among demographics, we included the respondent's gender (1: male; 0: female), age, rural living (1: rural area; 0: urban area), area-level context captured with regional fixed effects (i.e., Wales, Scotland, Northern Ireland, and English region), and type of household categorized into single-household living vs. living with a partner. We also included an indicator of social capital and two COVID-related variables: one in the NHS Shielding category, and the other related to changes of individuals' mobility due to COVID-19.

Among the socioeconomic variables, we included an indicator of respondents' living standards that may influence the probability of psychological distress, the probability of accessing formal and informal care, and the respondents' education level. Specifically, concerning the living standards, we included an indicator of respondents' subjective views of their financial situation as measured by the question, *"How well would you say you yourself are managing financially these days?"* Responses were coded with a five-point Likert scale with the following dimensions: (1) living comfortably; (2) doing alright; (3) just getting by; (4) finding it quite difficult; and (5) finding it very difficult. Thus, the score ranged between 1 and 5 with a higher score indicating a worse financial situation. Concerning the education level, three levels were considered: (1) lower education (no qualifications or basic qualifications—i.e., level 1–2 in the U.K. education system); (2)

medium education (level 3 in the U.K. education system or equivalent qualifications); and (3) higher education (i.e., levels 4–7 in the U.K. education system).

To account for respondents' "needs" unrelated to the pandemic itself and the associated lockdown, we also included information on their health status before the outbreak (U.K. HLS wave #10). The health-related variables concerned an indicator of general health, the self-assessed health (SAH), and the presence of a pre-existing mental condition. The SAH is supported by literature that shows a strong predictive relationship between people's self-rating of their health and mortality or morbidity (Idler & Benyamini (1997); Kennedy et al. (1998)). Moreover, the self-assessed health measurement correlates strongly with more complex health indices, such as functional ability or indicators derived from health service use (Undén & Elofsson (2006)). The following standard self-assessed health status question was asked: *"Would you say that in general your health is: 1) excellent, 2) very good, 3) good, 4) fair, 5) poor."* Since the answers could not simply be scored (for example as 1, 2, 3, 4, 5) because the true scale will not be equidistant between categories (O'Donnell et al. (2008)) according to previous literature (see, for instance, Balia & Jones (2008); Di Novi (2010); Di Novi (2013)), we dichotomized the multiple-category responses and constructed a binary indicator with a value of 1 if individuals reported that their health was fair or poor, and 0 otherwise (i.e., excellent, very good, or good). Pre-existing mental condition was identified using the GHQ-12 Caseness dummy indicator from U.K. HLS wave #10.

Concerning the indicator of social capital, we included a binary variable among the controls that takes value of 1 if respondents donated to a charity organization the year before the COVID-19 outbreak. Donating money to charity organizations is an indicator of social capital that we expect might influence informal care reception (and its disruption); moreover, it is also generally accepted as an altruistic act that may positively influence individuals' psychological health via experiencing well-being from helping (Dunn et al. (2008)).

Among the regressors, we included a dummy variable that indicated whether respondents were in the NHS Shielding category. In March 2020, the U.K. government introduced a Shielded Patient List (SPL)— i.e., a record of clinically vulnerable patients thought to be at higher risk of severe COVID-19 complications and COVID-19-related death. Those patients on the SPL were sent a notification by the NHS or the Chief Medical Officer to encourage them to stay in their homes and keep away from the rest of the population for 12 weeks. In our study, the NHS Shielding category (Yes/No) is ascertained from the COVID-19 Survey on the basis of a self-reported answer to the following question: "Have you received a letter, text or email from the NHS or Chief Medical Officer saying that you have been identified as someone at risk of severe illness if you catch coronavirus, because you have an underlying disease or health condition?" We expected that belonging to the NHS Shielding category might have directly affected informal and formal care reception as well as older individuals' mental health. Indeed, the elderly, especially those with cognitive decline and long-term conditions, need emotional support through informal networks and health professionals. As such, the lockdown might have created isolation and disruption of care along with a new set of challenges that could also affect other pre-existing health concerns, including mental health consequences (even though strict isolation was necessary to protect the elderly against the risks of the coronavirus). About 10% of our sample was notified as belonging to the NHS Shielding category as individuals extremely vulnerable to COVID-19.

Finally, we took advantage of a human mobility data set, the Google Covid-19 Mobility Report (GCMR) (Google (2020)) that reports changes in the mobility of Google Maps users across different destination categories (e.g., supermarkets, pharmacies, workplaces, residential areas) with respect to the first two months of 2020 (pre-COVID-19 outbreak). This data set is public and available in a variety of countries. Hence, we included both a measure of proximity to adult children and variation in mobility obtained by Google in our model, as well as an interaction term between them. These variables were assumed to be exogenous for the disruption of informal care.

We built a mobility index that combined different Google mobility categories into a single variable using two data sources: Understanding Society and the GCMR. Understanding Society considers 12 regions based on the Nomenclature of Territorial Units for Statistics (NUTS-1) Subdivision including Wales, Scotland, and Northern Ireland plus 9 regions in England (North East, North West, Yorkshire and The Humber, East Midlands, West Midlands, East, London, South East, and South West). We also used data on the total population in each region or the years 2015 to 2019 from the ONS (Office for National Statistics (2020)).

The GCMR provides daily mobility data for six location categories: residential, work-place, supermarket, and pharmacy (grocery), transit, retail, and parks (Google (2020)). Data are reported as percentage variations in the number of visits or time spent in each category with respect to a pre-COVID-19 baseline period defined from January 3 to February 6, 2020. Google chooses this reference period, and thus it cannot be modified. To protect users' privacy, absolute mobility values are not available.

Mobility data are available for each GCMR category for 108 sub-national regions (the GCMR's variable is called sub_region_1), from February 15, 2020 (the first available date in the data set) to August 14, 2020. We aggregated the GCMR data by week (we focused on March 23–29, 2020 for consistency with Understanding Society's questions on informal and formal care received and change in the care provision) and region (taking the weighted average across all counties in each region, with weights equal to their population sizes).

For each region analysed in our paper, we then extracted the most significant information from the different GCMR categories by merging them into a combined "Google mobility index" (see Basellini et al. (2021)). In other words, we worked with two dimensions (categories and regions) simultaneously. We performed a principal component analysis (PCA) of the mobility data and extracted the first component for the region, which is identified as using the component with the largest proportion of explained variance as criteria. Accordingly, we built a Google mobility index (*Gmobility*) retaining most of the information regarding mobility during the focal week. In constructing the index, we considered five location categories instead of six dimensions; specifically, we did not include the PCA residential category because it was missing too many values. The Google mobility index was standardized (see also Basellini et al. (2021)) for ease of interpretation.

The multivariate probit estimation was performed using the STATA 17 software and the use of the simulated maximum likelihood estimation method (see Cappellari & Jenkins (2003)).

2.4 Results and discussion

Table 2.2 shows a simple descriptive analysis that presents sample means and standard deviations for the variables used in the model (48% male; mean age: 72 years). Note the prevalence of psychological distress based on the GHQ-12 Caseness scoring, which increased from 13.7% at the time of wave #10 to 26.4% at the peak in April of 2020. About 4% of respondents reported that they experienced informal care disruption, and approximately 3% reported formal care disruption (as previously stated). Approximately 21% of the respondents reported fair or poor health before the onset of the pandemic.

Table 2.3 presents the results of the multivariate regression model with exclusion restrictions (the model without exclusion restrictions is included in the Appendix). Columns 1 and 2 report the estimated marginal effects for a disruption in informal care and formal care respectively, and Column 3 reports those respondents with psychological distress.

Starting with Column 1, the probability of informal care disruption decreases with age and for males. It is not significantly affected by the COVID-19 high-risk indicator (NHS Shielding category) for pre-existing mental health conditions, but instead increases with worsening pre-existing, self-reported general health conditions.

Table 2.3, Column 2 shows that formal care disruption is significantly and positively associated with variables that indicate a higher risk of adverse health outcomes if one contracts COVID-19. That is, the probability of formal care disruption increases with age and worsening pre-existing, self-reported health, and mental health conditions according to the COVID-19 high-risk indicator used in our study (i.e., being clinically extremely vulnerable to the COVID-19-NHS Shielding category). In general, these results confirm that older adults with pre-existing health conditions and for whom the consequences of catching the virus may be more serious faced the greatest social restrictions and stringent advice to stay at home. These adults were also more likely to experience a reduction of care, particularly in terms of community services. In such cases, formal care disruption was justified by the aim of protecting them from contracting COVID-19.

As expected, during the pandemic, the likelihood of informal care disruption was higher when adult children did not live close to their parents and for respondents without friends in their local area (according to estimated marginal effects of 1.3% and 3.8%, respectively). Due to movement restrictions and lockdowns, older adults remained isolated in their homes with limited outside contact including those with non-cohabiting adult children and friends, which are considered critical factors in contributing to the spread of the virus (Arpino et al. (2021); Bayer & Kuhn (2020)). Table 2.3 also shows that the absence of any financial support increased the probability of formal care disruption by about 2%.

Finally, the indicator of social capital, as expected, appears to have a negative influence on informal care disruption with a marginal effect of about 1.7%, given the association between social capital and the greater relationships within a community (Makridis & Wu (2021)).

In terms of socioeconomic status, perceived lower financial stability is associated with disruption in both informal and formal care even though the marginal effects are relatively low; moreover, according to our results, a higher education level positively influences informal care disruption only, with a marginal effect of about 2%. Arguably, a higher level of education raises awareness of the virus and may be positively associated with engagement in all types of preventive behaviours—including complying with stay-at-home rules. This implies a higher probability of in-person contact disruption and consequently the informal care provision particularly among the oldest population that is more vulnerable to COVID-19 infections (Li et al. (2021)).

In reference to the structural equation (Column 3 in Table 2.3), our results show that formal and informal care disruption significantly increases the probability of psychological distress, with a marginal effect of about 10% and 21%, respectively. The disruption of routine community care provided by family members, friends, and especially those provided by paid caregivers or social services workers imposes a great psychological burden on older people. Although prompted by safety of the elderly, reduced home visits and disruption of regular care compromises their psychological well-being through isolation and unmet needs (Allen et al. (2014)).

Concerning the other variables included in the structural equation, our findings show that being male was associated with a lower probability of psychological distress during the COVID-19 outbreak with a marginal effect of around 10%. According to our results, while perceived lower financial stability increases the probability of suffering from psychological distress by about 6%, as expected, a higher education level seems to positively affect the probability of suffering from mental health conditions with a marginal effect of about 5%. A large part of the existing literature that has analysed the relationship between individuals' mental health and education supports the protective role of education (see, among others, Feinstein (2002); Chevalier & Feinstein (2006); Crespo et al. (2014); Di Novi et al. (2021)). Nevertheless, our results are in line with the most recent literature (Niedzwiedz et al. (2021); Daly et al. (2022); Pierce et al. (2020); Belo et al.

(2020)) that focused on mental health conditions following the COVID-19 outbreak. According to these contributions (that were mainly related to younger adults), groups most adversely affected in terms of psychological distress included women, younger adults, people from minorities groups, and those with a higher education level. The hypothesis is that the more educated groups were more likely to shift to remote work during the pandemic and, for some, this work was combined with home-schooling and resulted in an increased psychological burden (Niedzwiedz et al. (2021); Daly et al. (2022); Pierce et al. (2020)). Concerning older individuals, further research is needed to shed light on this finding. Arguably, a higher level of education in this setting may proxy for an increasing awareness for older adults that they are at higher risk for severe morbidity and mortality from COVID-19, a circumstance that may also bring anxiety and readjustments in daily life and are likely stressful for this population (see Belo et al. (2020)). Respondents' altruistic attitude, proxied by charitable donations in our study, contributes negatively to older adults' psychological well-being. This is consistent with recent research on altruism and mental health during the outbreak, suggesting that altruism does not serve as a protective mental health factor against the threat of COVID-19, as highly altruistic individuals are more likely to feel anxious and depressed due to their empathy towards infected people, and to the impossibility of helping others due to self-isolation regulations (Li et al. (2020)).

We estimate that a reduction of one standard deviation in the combined Google mobility index is associated with an increase of 1.4% in the probability of suffering from depression, which suggests that mobility limitations, as reflected by a decrease of movements, increases the likelihood of suffering from psychological distress. Finally, there exists a positive correlation between pre-existing health conditions, psychological distress (as measured by the SAH and GHQ-12 in 2019, respectively), and worsening mental health.

As previously discussed, we constructed a simultaneous equation model for three binary variables. The multivariate probit estimation allowed us to test for unobserved heterogeneity that may characterize the relationship between informal and formal care disruption and individuals' psychological distress. The unobserved heterogeneity is captured by the correlation between the error terms from the single equation models. Table 2.4 shows the correlation coefficients for the full recursive model. The null hypothesis of exogeneity is rejected in only one case. According to our results, there exists a negative statistically significant correlation between the disturbance of the formal care disruption equation and the structural equation for individuals' psychological distress—i.e., unobservable variables that increase the likelihood of depression and decrease the probability of disruption in formal care provisions. Arguably, the inability to access social support services due to COVID-19 contributes to worsening anxiety and depressive symptoms especially among the elderly affected by pre-existing mental health conditions. As such, the virus increases their demand of formal care support that in turn decreases the likelihood of formal care disruption.

2.5 Conclusions

The fallout from the COVID-19 pandemic continues to affect almost every aspect of our society. With no medicines or vaccines available during the first wave of the pandemic, governments relied upon non-pharmaceutical interventions (NPIs) such as lockdown policies. Although social distancing has reduced the rate at which infected individuals infect others, it has come at the cost of both an economic crisis as well as foregone benefits of physical social contacts that have profoundly reshaped LTC patterns. The pandemic has indicated a certain level of disruption in formal and informal caregiving, as care providers consider the possibility of transmitting the virus to the elderly. Social distancing has been necessary to protect older adults against the risk of severe infection and COVID-19-related death; however, such isolation may have created a new set of challenges affecting other pre-existing health concerns. It is well known that older people with unmet needs (as a potential consequence of informal and formal care disruption) cope with greater challenges and vulnerabilities correlated, in many instances, with poor mental health and anxiety (Komisar et al. (2005); Momtaz et al. (2012); He et al. (2015)). In this paper, we investigated how informal and formal care disruption due to the COVID-19 outbreak have affected older people's mental health. For the purposes of our analysis, we relied on individual-level data from the U.K. Household Longitudinal Study (U.K. HLS)—Understanding Society. We modelled the association between a disruption of formal and informal care received by the elderly and their mental health during the first wave of the COVID-19 pandemic by using a recursive simultaneous equation model for binary variables. According to our results, this disruption due to the COVID-19 emergency—and the aim of protecting the most vulnerable part of the population—has significantly affected older individuals' psychological distress.

With the U.K. addressing additional waves of COVID-19, and as a lesson for future pandemics, the potential impact of the disruption of long-term care on older individuals' mental health should be considered. Indeed, the possible benefits of mandatory lockdown in curbing the virus spread need to be carefully weighed against the potential psychological health costs. Successful use of isolation as a public health measure requires a realistic reduction in the negative effects associated with it, especially among more vulnerable groups.

Our paper has investigated the impact of disruption in informal and formal care on the elderly's mental health using data from the U.K. Household Longitudinal Study (U.K.HLS), Understanding Society. One limitation of this data set is that it did not allow us to study possible differences of the disruption impacts related to territories, age groups, and gender. The sample size must be larger to implement heterogeneity tests. This is left for future research.

Tables

Table 2.1: Variables names and definition

Variables names	Definition	Main Survey/ COVID-19 Survey
Mental Health Conditions/ Psychological Distress 2020 (GHQ>=3)	1 if GHQ-12 Caseness items score is greater or equal than 3 reflecting deteriorations in mental health, 0 otherwise	COVID-19 Survey w 1
Formal Care Disruption	1 if respondent did not receive formal care or received reduced formal care with respect to period before COVID-19 outbreak, 0 otherwise.	COVID-19 Survey w 1
Informal Care Disruption	1 if respondent experienced a decrease in the provision of care in the four weeks before the interview, with respect to the period before the outbreak of COVID-19, 0 otherwise.	COVID-19 Survey w 1
Age	continuous variable	COVID-19 Survey w 1
Male	1 if male, 0 female	COVID-19 Survey w 1
Rural	1 if lives in a rural area, 0 urban area	Main Survey w 10
England	1 if lives in England, 0 otherwise	Main Survey w 10
Wales	1 if lives Wales, 0 otherwise	Main Survey w 10
Scotland	1 if lives in Scotland, 0 otherwise	Main Survey w 10
Northern Ireland	1 if lives in Northern Ireland, 0 otherwise	Main Survey w 10
Living with partner	1 if lives with partner, 0 if alone	Main Survey w 10
Lower education	1 if completed level of education is null or 1-2 of U.K. education system, 0 otherwise	Main Survey w 10
Medium education and other qualification	1 if completed level 3 of U.K. education system or other qualification, 0 otherwise	Main Survey w 10
Higher education	1 if completed level of education is 4-7 of U.K. education system, 0 otherwise	Main Survey w 10
Subjective view of financial situation	five-point Likert scale with the following dimensions: 1) living comfortably; 2) doing alright; 3) just getting by; 4) finding it quite difficult; and 5) finding it very difficult.	Main Survey w 10
NHS shielding category	1 if NHS told him/her that he/she is at severe risk of COVID-19 infection, 0 otherwise	COVID-19 Survey w 1
Charitable donations	1 if respondent donates money to charity, 0 otherwise	Main Survey w 10
Non-proximity with non-cohabitating children	1 if respondent lives more 30 than minutes journey time of their children, 0 otherwise	Main Survey w 10
Gmobility index	Google mobility index obtained from the principal component analysis. It was normalized to lie between 0 (lowest bound) and 1 (highest bound)	Google mobility data
Pre-existing Poor Health Conditions (SAH)	1 if SAH is fair or poor, 0 otherwise	Main Survey w 10
Pre-existing Mental Health Conditions/ Psychological Distress 2019 (GHQ>=3)	1 if GHQ-12 Caseness items score measured in 2019 is greater or equal than 3 reflecting deteriorations in mental health, 0 otherwise.	Main Survey w 10
No friends living in local area	1 if the respondent has no friends living in local area, 0 otherwise.	Main Survey w 9
Who deals with formal care payments	1 if the respondent deals with formal care payments partly or entirely by herself, 0 otherwise.	Main Survey w 9

Table 2.2: Descriptive Statistics

	Mean	SD
Mental Health Conditions/		
Psychological Distress (GHQ >= 3)	0.264	0.441
Formal Care Disruption	0.027	0.161
Informal Care Disruption	0.041	0.198
Age	72.19	5.446
Male	0.481	0.500
Rural	0.334	0.472
England	0.819	0.385
Wales	0.059	0.235
Scotland	0.089	0.285
Northern Ireland	0.033	0.177
Living with partner	0.746	0.435
Lower education	0.275	0.447
Medium education and other qualification	0.277	0.447
Higher education	0.448	0.497
Subjective view of financial situation	1.605	0.727
Charitable donations	0.825	0.380
Pre-existing Poor Health Conditions (SAH)	1.605	0.727
Non-proximity with non-cohabiting children	0.103	0.304
NHS shielding category	0.104	0.305
Pre-existing Mental Health Conditions/		
Psychological Distress 2019 (GHQ >= 3)	0.137	0.344
No friends living in local area	0.034	0.180
Who deals with formal care payments	0.079	0.270
Observations	3,721	

Table 2.3: Marginal Effects from the Recursive Multivariate Probit Model

	Informal Care Disruption	Formal Care Disruption	Mental Health Conditions (GHQ>=3)
Age	-0.002**	0.001***	-0.002
	(0.001)	(0.000)	(0.001)
Male	-0.021***	0.008	-0.104***
	(0.007)	(0.005)	(0.014)
Rural	0.000	-0.002	-0.004
	(0.007)	(0.006)	(0.015)
Wales	-0.025***	0.002	-0.057**
	(0.009)	(0.012)	(0.028)
Scotland	0.004	0.003	-0.008
	(0.011)	(0.010)	(0.024)
Northern Ireland	0.007	0.006	-0.029
	(0.020)	(0.016)	(0.039)
Living with partner	0.003	-0.003	-0.058***
	(0.007)	(0.006)	(0.017)
Medium and other education	0.021*	0.008	-0.012
	(0.011)	(0.007)	(0.018)
Higher education	0.019**	-0.003	0.045***
	(0.009)	(0.006)	(0.017)
Subjective view of financial situation	0.009**	0.006*	0.057***
	(0.004)	(0.003)	(0.010)
Pre-existing Poor Health Conditions (SAH)	0.015	0.033***	0.051***
	(0.010)	(0.008)	(0.019)
NHS shielding category	0.004	0.019**	0.014
	(0.011)	(0.009)	(0.023)
Charitable donations	-0.017**	-0.009	0.040**
	(0.006)	(0.007)	(0.018)
Gmobility Index	0.003	-0.000	0.014*
	(0.004)	(0.003)	(0.007)
Pre-existing Mental Health Conditions (GHQ>= 3)	0.008	0.023**	0.264***
	(0.010)	(0.009)	(0.025)
Non-proximity with non-cohabiting children	0.013**		
	(0.006)		
No friends living in local area	0.038**		
	(0.016)		
Deals with care payments by herself		0.018**	
		(0.010)	
Informal care disruption			0.100***
			(0.037)
Formal care disruption			0.212***
			(0.051)
N	3721	3721	3721

[]

Table 2.4: Correlation Coefficients from the Recursive Multivariate Probit Estimation

	Informal Care Disruption	Formal Care Disruption	Mental Health Conditions/ Psychological Distress (GHQ >= 3)
Informal Care Disruption	1	-0.094 (0.081)	-0.018 (0.054)
Formal Care Disruption		1	-0.096* (0.055)
Mental Health Conditions (GHQ >= 3)/ Psychological Distress (GHQ >= 3)			1

Appendix

Sensitivity Analysis

In our main analysis, elderly's psychological distress is measured by the 12-items Generalised Health Questionnaire (GHQ-12 Caseness), and respondents scoring 3 or more out of a possible total of 12 are considered at risk of anxiety and/or depression. First, we re-run the model setting the GHQ-12 Caseness threshold at 4, to identify higher intensities of mental health problems and how they are related to formal and informal care disruption (see Davillas & Jones (2021)). Secondly, we re-run the model by considering as dependent variables binary indicators for each of the 12 items that comprise the GHQ-12 Caseness questionnaire.

1A. Different Threshold for the Generalised Health Questionnaire (GHQ-12)

As stated before, we rely on the same specification of the main model, with one reduced form (informal care disruption) and two structural equations (formal care and mental health), while we move the threshold identifying mental health conditions at 4 symptoms. Results confirm those of the main analysis. According to our results (columns 1 and 2 of Table 2.5), elderly who live more than 30 minutes away from their children or who do not have any friend living in the same area are more likely to experience informal care disruption; this is especially important in periods of movement restrictions. Elderly with pre-existing health conditions are more affected by social restriction when it comes to formal care provision, thus being more likely to experience a reduction of care; whereas, this effects is no longer significant in the regression of informal care disruption.

Moreover, older adults who deal with care payments partly or totally by themselves, are more exposed to formal care disruption. Finally, social capital decreases informal care disruption, while a perceived lower financial stability is associated with disruption in both forms of care.

With reference to the structural equation for psychological distress (column 3 in Table 2.5), results show that both informal and formal care disruption significantly raises the likelihood of experiencing psychological distress among elderly with higher intensities of mental health problems. Thus, our findings seem to support the hypothesis that, among the group of elderly people with more critical psychological conditions, the disruption of routine care provided by both informal caregivers as well as paid care workers or social services, due to lockdown policies, are concurrent causes of worsening of psychological distress.

Table 2.5: Marginal Effects from the Recursive Multivariate Probit Model

	Informal care disruption	Formal care Disruption	Mental Health Conditions/Psychological Distress (GHQ>=4)
Age	-0.002**	0.001***	-0.002
	(0.001)	(0.000)	(0.001)
Male	-0.021***	0.007	-0.104***
	(0.007)	(0.005)	(0.014)
Rural	0.000	-0.002	-0.004
	(0.007)	(0.006)	(0.015)
Wales	-0.025***	0.002	-0.057**
	(0.010)	(0.012)	(0.028)
Scotland	0.004	0.003	-0.008
	(0.011)	(0.010)	(0.024)
Northern Ireland	0.006	0.005	-0.029
	(0.020)	(0.016)	(0.039)
Living with partner	0.003	-0.003	-0.058***
	(0.007)	(0.006)	(0.017)
Medium and other education	0.021**	0.007	-0.012
	(0.011)	(0.007)	(0.018)
Higher education	0.019**	-0.003	0.045***
	(0.009)	(0.006)	(0.017)
Subjective view of financial situation	0.009**	0.006*	0.057***
	(0.004)	(0.003)	(0.010)
Pre-existing Poor Health Conditions (SAH)	0.015	0.033***	0.051***
	(0.010)	(0.008)	(0.019)
NHS shielding category	0.004	0.019**	0.014
	(0.011)	(0.009)	(0.023)
Charitable donations	-0.017*	-0.008	0.040**
	(0.010)	(0.007)	(0.018)
Proximity with non-cohabiting children	0.013**		
	(0.006)		
Gmobility Index	0.003	-0.000	0.014*
	(0.004)	(0.003)	(0.007)
Pre-existing Mental Health Conditions/ Psychological Distress 2019 (GHQ >= 4)	0.008	0.028***	0.264***
	(0.011)	(0.010)	(0.025)
No friends living in local area	0.037**		
	(0.016)		
Deals with care payments by herself		0.018*	
		(0.010)	
Informal care disruption			0.100***
			(0.037)
Formal care disruption			0.212***
			(0.051)
N	3721	3721	3721

2 A. The Different Dimensions of the GHQ-12 Caseness As second sensitivity analysis, we define a different outcome variable. We take binary indicators for each of the 12 questions that comprise the GHQ-12 Caseness questionnaire and re-run the model again (see Davillas & Jones (2021)). Performing this evaluation allows us to verify if the model is well identified and to further investigate the relation between each of the GHQ dimensions and formal and informal care disruption, identifying which are more related to one or the other dimension of care disruption.

The twelve dimensions of GHQ-12 are concentration, loss of sleep, playing a useful role, ability to make decisions, coping under strain, overcoming difficulties, enjoying activities, facing up problems, feeling depressed or unhappy, feeling worthless and general happiness. As explained in Subsection 2.3.1, responses are answered on a four-category scale: "not at all", "no more than usual", "rather more than usual", "much more than usual". In order to create the binary indicator, for each dimension, we attribute the value 1 to the two categories indicating the most depressed states and 0 to the remaining two categories, reflecting better mental health (see Davillas & Jones (2021)). We run again the multivariate probit model, substituting one at a time each binary indicator as outcome variable.

First of all, this analysis confirms that the model is well identified. First, in all regressions, distance from adult children and friends are statistically significant: the likelihood of informal care disruption is higher when adult children or friends do not live closer to the elderly, especially during the implementation of movement restrictions and lockdowns. Second, dealing with care payments is significant with positive sign in all regressions, suggesting that elderly are more likely to experience disruption of formal care when they are supporting the economic cost of the service partly or totally.

Third, formal care disruption is statistically significant with positive sign in eleven out of twelve regressions, suggesting a positive, consistent relation between reduction or interruption of formal provision and worsening of the different dimensions of mental health. This evidence is not found only in the case of the item "Believe worthless". On the other hand, informal care disruption is positively associated with the items "Constantly under strain" (at 5% level), "Enjoy day to day activities" (at 5% level), "Feeling unhappy or depressed" (at 5% level) and negatively related to "Believe worthless" (at 10% level). In other words, as we expected, elderly who suffer disruption of informal care and social distancing are more exposed to depression. According to our results, these four dimensions of psychological distress are the most affected by informal care disruption and are the items that drive the impact of informal care disruption on the aggregate GHQ-12 Caseness score.

Table 2.6: Multivariate Probit Model of the 12 items of the GHQ-12 – Estimated Marginal Effects

	Concentration	Loss of sleep	Playing a useful role	Capable of making decisions	Constantly under strain
Informal care disruption	0.0339	0.0366	0.0609	-0.0179	0.0673*
	(1.13)	(1.26)	(1.67)	(-1.03)	(2.17)
Formal care disruption	0.270***	0.128**	0.113*	0.183***	0.106*
	(5.39)	(2.93)	(2.33)	(4.33)	(2.56)
N	3721	3721	3721	3721	3721

	Problem overcoming difficulties	Enjoy day to day activities	Ability to face problems	Unhappy or depressed	Losing confidence
Informal care disruption	0.0279	0.103*	0.0108	0.102**	-0.00716
	(1.22)	(2.51)	(0.55)	(2.91)	(-0.39)
Formal care disruption	0.136***	0.114*	0.108**	0.120**	0.130***
	(3.47)	(2.20)	(3.09)	(2.61)	(3.44)
N	3721	3721	3721	3721	3721

	Believe worthless	General happiness
Informal care disruption	-0.0305**	-0.00327
	(-3.24)	(-0.11)
Formal care disruption	0.0249	0.120**
	(1.08)	(2.65)
N	3721	3721

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3.NEIGHBOUR COHESION, SOCIAL RELATIONS AND LONELINESS IN TIMES OF COVID-19: EVIDENCE FROM ENGLAND.

Abstract

This paper provides evidence on the link between pre-pandemic social interactions and the impact of COVID-19, and of the restrictions implemented by the governments to limit its spread among the population, on the sentiment of loneliness. By exploiting individual-level data from the U.K. Household Longitudinal Study (U.K.HLS), Understanding Society, two research questions are investigated. First, is neighbourhood social cohesion a protective factor for loneliness? Second, how do certain characteristics of people's social networks impact loneliness? We model the association between social and relational variables and loneliness throughout the COVID-19 pandemic using linear and probit model specifications. Our findings, by documenting the protective role of social cohesion and social relations against loneliness, suggest the importance to foster and maintain social connections, even during times of pandemics.

3.1 Introduction

Since the beginning of coronavirus pandemic, efforts undertaken to contain the spread of the virus dramatically disrupted social life. Lockdown restrictions implemented by governments worldwide limited people's movements and social life. While extremely effective in preventing the spread of the contagion, containment measures raised concerns on the adverse effects on people's overall well-being (Brooks et al. (2020)). In particular, social isolation is known to be a precursor for feelings of loneliness (Russell et al. (1980); Beutel et al. (2017)), that, in turn, is associated with a plurality of negative health outcomes (Hawkley & Cacioppo (2010); Steptoe et al. (2013)). This chapter investigates the connection between social relations and the impact of coronavirus pandemic and restrictions implemented by the UK government on the sentiment of loneliness. The aim is to analyze how social relations influence loneliness before and throughout the pandemic. We focus on three variables describing relations and interactions: social cohesion at neighbor level, number of close ties and time spent chatting with friends on social web-sites. Our results show the importance of social connections in times of pandemic, suggesting that neighborhood cohesion appears supportive for the elderly, whereas a large network of friends is particularly meaningful for young people. Conversely, daily, prolonged exposure to online interactions seems detrimental to individual's well-being. Our findings call for initiatives to foster social connections, even during periods of pandemics. This chapter is organized as follows. First, background evidence from the UK is described and the objectives of the research are declared (Subsection 3.1.1, 3.1.2). Then, research gaps are deeply discussed (3.1.3). Afterwards, empirical methods (Section 3.2), data and variables are explained (Section 3.3). Results are reported in Section 3.4, finally, onclusions and policy implications are discussed (Section 3.5).

3.1.1 Background

In the U.K., a national lockdown was announced by the government on March 23rd, 2020, with immediate closures of schools, businesses, and public facilities (UK Government (2020)). People were strongly advised to avoid face-to-face contact with anyone outside their household, work from home, stop travelling and avoid populated areas (Cameron-Blake et al. (2020)). Since that period, the U.K. population has undergone a significant decrease in, and sometimes a total lack of, face-to-face social interaction. As lockdown orders began to lift in May 2020, considerable restrictions on social life remained, such as maintaining social distance and avoid gatherings (Cameron-Blake et al. (2020)). Containment measures were further reinforced with the three tier "Covid alert levels" system, following the rapid increase in the number of cases in autumn 2020 (UK Government (2020)). On November 5th, 2020, the government declared a second national lockdown in England for four weeks, followed by a third, that began on January 6th, 2021. Concomitantly, Scotland entered its second national lockdown on January 5th. Restrictions were not eased until March 2021.

As efforts were made to protect the population, particularly those at higher risk, and safeguard their physical health, apprehensions began to surface regarding the potential adverse impact of these restrictions on people's overall well-being. (Brooks et al. (2020)). The U.K. Academy of Medical Sciences reported that, among the U.K. public, fears surrounding the psychological damage of COVID-19 were rated above that of physical wellbeing (Cowan (2020)). Indeed, containment measures meant that people were left without resources for socioemotional, physical, and spiritual engagement (Robinette et al. (2021)). "Stay-at-home" orders and social isolation from friends and family members caused stronger feelings of loneliness, that in turn lead to heightened symptoms of depression (Krendl & Perry (2020)).

3.1.2 Objectives

While social isolation and loneliness are distinct concepts, research has shown that they are closely linked (Russell et al. (1980)), with social isolation often serving as a precursor to feelings of loneliness (Beutel et al. (2017);Menec et al. (2020)). Social isolation is described as the absence of social interactions, contacts, and relationships with others, while loneliness is defined as "the unpleasant experience that occurs when a person's network of social relations is deficient in some important way, either quantitatively or qualitatively" (Perlman & Peplau (1981), p. 31). While being important per se, as it relates to human wellbeing, loneliness is associated with multiple negative health outcomes, resulting in increasing morbidity and mortality (Hawkley & Cacioppo (2010); Steptoe et al. (2013); Gale et al. (2018); Jarach et al. (2021); Wenger et al. (1996). In the U.K., prior to the

COVID-19 pandemic, the government had identified loneliness as a major public health issue that should be considered as an epidemic (Jeste et al. (2020)). As such, the potential effects of COVID-19 on loneliness are not just relevant from an individual perspective, but also in terms of social cohesion and, in turn, for the mental and physical health outcomes that could occur as a result. Thus, there have been calls to ascertain how the COVID-19 pandemic has affected loneliness (Armitage & Nellums (2020); Banerjee (2020)). In particular, it is relevant to understand how social interactions affect loneliness, during COVID-19 emergency.

Hence, we contribute to the existing literature by providing some first evidence, to the best of our knowledge, on the link between pre-pandemic social interactions and the impact of COVID-19, and of the restrictions implemented by the governments to limit its spread among the population, on the sentiment of loneliness. Specifically, the aim of this paper is to answer the following questions:

1. Is greater neighbourhood social cohesion a protective factor for loneliness?
2. How do certain characteristics of people's social networks impact loneliness? In particular, we analyse the effect of individual's close ties and mode of communication on loneliness.

Hence, we focus on neighbourhood social cohesion, that describes the relationships and social support that individuals perceive in their local community (Cohen & Wills (1985)). As we discuss in Subsection 3.3, this measure is based on several items addressing the extent to which individuals can, as an example, call on neighbours for social support (e.g., friendship, information, instrumental, and emotional support (Cohen & Wills (1985)). Moreover, we will analyse the impact on loneliness of individual's personal relationships and mode of communication; specifically, as we clarify in Subsection 3.3, we consider respondent's number of close friends, and the hours spent chatting with friends on social website, i.e., the magnitude and quality of individual's social network.

For our analysis, we build an integrated dataset by merging two datasets in the U.K. Household Longitudinal Study (UKHLS), a large, representative sample of U.K. individuals, i.e. the Main Survey and the COVID-19 Survey from Understanding Society. By relying on numerous waves of data, we have at our disposal respondents' information on the pre-pandemic period, on the immediate coronavirus outbreak, and on the whole course of the pandemic (with the related policies on social restrictions) until September 2021. This allows us to construct longitudinal models to assess the effect of neighbour social cohesion and social relations variables on loneliness, before and during the pandemic.

Our results contribute to a better understanding of the protective role of neighbour and social relations against loneliness during coronavirus emergency, and, hence, they have some policy implications. First, since we have obtained some empirical evidence that social cohesion in the neighbourhood where one lives is an important moderator of loneliness, even in times of pandemic, social policies at the local level should increase opportunities for interaction in neighbourhoods. Such opportunities could be cultural events, volunteering activities, entertainment and meeting occasions that could bring together families, young people, and elderly, creating new relations and fostering existing ones at community level; increasing social cohesion at the local level may act as a deterrent in case of future pandemics.

Secondly, if public authorities need to adopt policies restricting social relations in the future, they should design forms of restriction at local level taking into account the importance of social relations. While forbidding inside and outside gatherings with many participants is effective in avoiding contagion, meeting people in the open air while maintaining social distance and masks may be, on one side, efficacious in shielding individuals from virus transmission, and, on the other side, allowed people to see and talk with relatives and friends living close by, with important benefits in terms of social and emotional support. A better-designed policy that takes into account the impact of social cohesion also has the advantage of increasing the effectiveness of vaccines in the presence of future pandemics, since the study by Gallagher et al. (2022) demonstrated, for the first time, that lower social cohesion is associated with lower antibody response to the COVID-19 vaccination in the U.K., and that vaccine responsiveness is influenced by recipient's psychosocial experiences.

3.1.3 Research gaps

The association between psychosocial factors and loneliness during a pandemic is still largely understudied. Specifically, we identify the following gaps in the literature. The first gap regards the role that protective collective factors may have during pandemics

(O'Donnell et al. (2022)). Research to date mainly focused on individual protective factors, intended as characteristics and resources an individual possesses that may shield against poor mental health and promote general wellbeing (O'Donnell et al. (2022)). Among these, social support and coping strategies such as positive thinking and resilience are the most often investigated factors, and recent evidence documents their strong protective role for mental health during periods of lockdowns (Budimir et al. (2021); Nitschke et al. (2021); Ye et al. (2020)).

Conversely, collective protective factors have the potential to impact and safeguard a wider population; one such collective factor is social cohesion, defined as the sense of connectedness to a group and its members (Chan et al. (2006)). In the context of health research, social cohesion has gained increasing attention in recent years, as positive social relations offer collective resources to manage health challenges and support mental health (Fiori et al. (2016); Thoits (2010)). Specifically, existing literature demonstrated that neighbourhood social cohesion has a beneficial and protective effect on individuals' mental health and general wellbeing during collective crisis such as natural disasters (Townshend et al. (2015); Ludin et al. (2019)).

Although the extent to which neighbourhoods have played a role during the COVID-19 pandemic is yet to be fully understood, their importance may have been amplified due to limitations on people's movements, which have restricted their ability to engage with broader social networks. We were able to identify only two studies that focus on neighbourhood social cohesion and its effect on mental health and loneliness during coronavirus emergency (O'Donnell et al. (2022) for Australia and Robinette et al. (2021) for the US).

The study by O'Donnell et al. (2022) aims at quantifying the impact of a second lockdown in 2020 in the Australian city of Melbourne on levels of depression, anxiety and loneliness and analyses whether social relations in the neighbourhood may buffer against effects of lockdown. They document that lockdown increased depressive symptoms and feelings of loneliness and that neighbourhood social relations are strongly, negatively associated with mental health. Moreover, for people whose perceived number of relations was larger than average, the increase in depressive symptoms due to the lockdown was relatively smaller than the rest of individuals. A limitation of this study is the fact that the survey was entirely conducted during the period of the global pandemic, with three waves of data collected between May and October 2020. Thus, measures of mental health and wellbeing are likely to be strained across all waves and insights are provided on a very limited time span.

The work by Robinette et al. (2021) tests the hypothesis that neighbourhood relations are associated with fewer symptoms of depression during lockdowns. While the variable of interest is again social cohesion at community level, the outcome variable considered by the authors is depression; thus, while this study uncovers the health policy implications of neighbour cohesion during periods of absence of social interactions, it does not uncover the association between cohesion and loneliness, which is the aim of our work. Findings show, first, that individuals who perceive their neighbourhoods as more cohesive report fewer symptoms of depression during the pandemic; and, second, that sheltering at home during the lockdown is not related to self-reported depressive symptoms for those who view their neighbourhood as cohesive. Results suggest that, during times when social support from members of people's usual network are less accessible, support from neighbours may alleviate some of the burden related to local, national, and international crisis. Two major limitations of this study regard the sample, that while being large, is not a probability sample, and the study cross-sectional design, that allows to establish associations, but not causality.

The second research gap regards the association between people's social network and loneliness, which until now has been mainly analysed during periods of social stability. Evidence shows that having more close ties over few confidants is associated with lower levels of loneliness in general (Hawkley & Cacioppo (2010); van Tilburg (1990)); furthermore, the composition of social networks also seems to matter: individuals relying especially on family ties appear at higher risk of loneliness compared to those with more heterogeneous relations (Dykstra (1990); Silverstein et al. (1996)). Interestingly, findings from a study on hurricane Katrina survivors find that those with larger social networks experience less financial, physical and health disturbances because of the disaster (Forgette et al. (2009)).

As far as we know, only one US study analyses the relation between social network characteristics of individuals and loneliness during 2020 coronavirus pandemic, as well as how these characteristics have changed following a period of profound social isolation (Kovacs et al. (2021)). Authors recruit survey participants from a Yale University local research pool and analyse a small sample of 189 people. Authors found that having fewer than five close ties is associated with a higher increase in loneliness, uncovering the heterogeneous effects of lockdown on the population from the point of view of social connectedness. Interestingly, the study investigates the association between modes of communication and loneliness, as the pandemic offers a unique opportunity to study whether technologically mediated communications act as an effective substitute for face-to-face interactions. Little evidence is found that non face-to-face communication such as videoconferencing and text messaging are not an effective substitute for in-person interactions (Kovacs et al. (2021)).

Limitations of this research are related to small sample size and to self-selection of respondents in the survey, as this was a convenience sample, meaning that whoever signed up to the local university's participant pool was going to be surveys and the group was clearly not representative of the general US population. Moreover, all participants come from the same specific state and county and, hence, were all exposed to the same isolation requirements. Our contribution investigates instead a larger sample, that is representative of the population and includes respondents coming from an entire nation, while also covering a longer time span. Moreover, our analysis considers a larger set of control variables, including information on the type of household, area of residence and physical health. Finally, as we have at our disposal several waves of analysis throughout the pandemic, we are able to study the association between loneliness and social interactions under different requirements of lockdown and social distancing.

In conclusion, we contribute in several ways to existing research on various themes related to COVID-19 emergency. First of all, we provide new evidence on the protective role of collective social relations and social interactions in times of crisis. Secondly, as the discussion on the serious strains that the pandemic left has just begun, we expand the reflection on the potential adverse effects of containment measures on people's feelings of loneliness. Third, as regards our data, we are able to rely on a longitudinal, representative and rich dataset, that makes possible to cover basically the entire period of the pandemic. Fourth, we are able to provide new insights: elderly benefit especially from relations at neighbor level, while having more friends over few confidants is particularly meaningful for young people.

3.2 Empirical methods

In this section, we present a basic empirical model to investigate the impact of social cohesion and social relations on loneliness (*LONE*), i.e., the following relation:

$$LONE = F(S_1, S_2, X) \tag{3.1}$$

where F is the function describing the relation between S_1, i.e., neighbour social cohesion (*COHESION*) and S_2, i.e., social relations variables, namely individual's close ties (*TIES*) and time spent chatting with friends on social website (*CHAT*); X is the vector of control variables (time varying as well as time invariant) that we will present later in Subsection 3.3. The baseline model is as follows:

$$LONE_{i,t} = \beta_0 + \beta_1 S_i + Wave_t + \Sigma(\beta_{2t} S_i * Wave_t) + X_i\gamma + \mu_{it} \tag{3.2}$$

where, $i = (1, ...n)$ individuals; $t = (1, ...k)$ time periods. The outcome variable *LONE* is a dummy taking value 1 if the respondent feels lonely "Often" or "Some of the time", 0 if "Hardly ever, never", as detailed in Section 4. Variables (S_i) are *COHESION* (Model 1), *TIES* (Model 2), and *CHAT* (Model 3). Variable $Wave_t$ includes wave fixed effects, leaving year 2018 as the base category; it captures different waves of the UKHLS Survey, hence, it represents a fixed effect. β_2 captures the interaction between the variable of interest (i.e., *COHESION, TIES, CHAT*) and wave dummies. Thus, it is an estimate of the association between loneliness and social cohesion/social relations indicators before the pandemic and during different moments of COVID-19 crisis, since the first wave during the pandemic is related to April 2020, and the last in our period of analysis is September 2021. Therefore, we observe how perceptions and threats regarding the pandemic, on the one hand, and, tightening or relaxation of restrictions implemented by public authorities, on the other, interacted with social relations variables, to affect and change loneliness.

Regarding control variables, we include several socioeconomic and health status indicators, as we explain in Subsection 3.3. Standard errors are clustered at the individual level. The analysis was implemented in Stata17 (StataCorps, Texas).

We provide evidence regarding Eq.(3.2) using two estimation methods: (1) linear probability model for a first inspection, and (2) probit model, as our dependent variable

LONE is constructed as a dichotomous indicator, as we detail in section 3.3.

In estimating equation 3.2, we need to take into account an important econometric challenge: the possible reverse causality between loneliness and social interaction variables. We tackle this problem by including variables that have been measured before the outbreak of coronavirus, specifically, in 2018 (*LONE* is measured across all waves, as we explain later in section 3.2.1). Hence, *COHESION*, *TIES* and *CHAT* are not influenced by COVID-19 emergency and our model does not suffer from reverse causality issues.

The identification of the model needs further discussion. The three independent variables of interest, i.e. *COHESION*, *TIES* and *CHAT* may be endogenous, since it might be the case that some unobservable variables not included in the model influence these indicators and the outcome variable *LONE* simultaneously. While these three variables were measured in Wave 2017-2018, prior to variable *LONE* , this is not sufficient to exclude the issue of endogeneity due to unobservable factors. In this case, implementing an IV strategy is the correct approach to solve the bias (see Appendix).

We clarify that we measure the impact of pre-pandemic social interaction variables on loneliness, to understand whether these factors warded against the threat of loneliness during a collective crisis, with periods of prolonged isolation (see Hansen et al. (2021); Sato et al. (2022); Kovacs et al. (2021)). Thus, while we acknowledge that the pandemic was a shock for social cohesion and social relations in the U.K. (Borkowska & Laurence (2021)), the objective of this study is to analyse the association between social interaction variables measured before the emergency and loneliness, rather than changes in people's perceptions of cohesion and relations. Moreover, social networks and friends are long-lasting relations.

3.3 Data, variables and descriptive statistics

We use individual level data from Understanding Society: the U.K. Household Longitudinal Study (UKHLS), a nationally representative household panel study of the U.K. population (2009-2022). Understanding Society includes a special COVID-19 Study, investigating experiences and reactions of the U.K. population to the COVID-19 pandemic. The COVID-19 Study sample comprises active respondents from the Main Study, therefore data can be linked to answers provided in previous UKHLS waves. For our analysis, we combined 11 waves. Wave 9 (fieldwork: 2017–2019) and 10 (2018–2020) from the

Main Survey and all available COVID-19 data: Wave 1 (Late April 2020), 2 (Late May 2020), 3 (Late June 2020), 4 (Late July 2020), 5 (September 2020), 6 (November 2020), 7 (January 2021), 8 (March 2021), 9 (September 2021). All waves contain a 'loneliness module', regarding respondents' feelings of loneliness. The UKHLS is representative of the UK population.

We restrict our analysis to England, in order to have a homogeneous sample in terms of people's perception of loneliness; indeed, existing research on culture and social behaviours suggests that cultures significantly differ in the meaning of social behaviours and in the values of interpersonal relationships (Rokach et al. (2001); Barreto et al. (2021)). As the U.K. is characterized by significant differences in population density across the four countries and by an uneven distribution of inhabitants within countries, it is reasonable to believe people's perception of loneliness is strongly affected by these factors. For instance, most local authorities in Scotland and Wales have lower population densities than is typical of the U.K., with fewer than 50 people per square kilometre in the most rural local authorities (Office for National Statistics (2020)); in Scotland, the majority of people living in remote rural areas do not have access to key services, such as a shopping centre or a secondary school, within a 15 minute's drive (Scottish Government (2021)). Perception of loneliness may be rather different between Scotland and England. Therefore, we decided to restrict the analysis sample to residents of England only, to ensure that we were analysing a homogenous sample in terms of perception of loneliness. After correcting for missing values, the final sample consists of 64,248 observations (the initial dataset comprised 74,371 observations).

We focus on three variables: loneliness, social cohesion and social relations. To measure loneliness, we consider the following question, available across all waves of data: "In the Last 4 weeks, how often did you feel lonely?" There are three answers: 1. Hardly ever, never 2. Some of the time 3. Often. Existing research found that this single-item direct question can be considered a good proxy for loneliness, both in COVID-19 related studies as well as in previous research (Ong et al. (2016); Gallagher & Wetherell (2020); Gallagher et al. (2022)). Our dependent variable is *LONE*, a dummy taking value 1 if the answer is "Some of the time" or "Often", 0 "Hardly ever, never". We outline that we measure the feeling of loneliness, that is, individuals' self-reported sentiment of loneliness. We are not relying on an objective measure: we are interested in individual's perception.

For social cohesion, we use an index based on Buckner's Neighbourhood Cohesion Instrument[1]) (Buckner (1988)), which measures the agreement level of the individuals to the following 8 statements. 1) "I plan to remain a resident of this neighbourhood for a number of years"; 2) "Can borrow things from neighbours"; 3) "If I needed advice about something I could go to someone in my neighbourhood."; 4) "I regularly stop and talk with people in my neighbourhood."; I think of myself as similar to the people that live in this neighbourhood."; "I feel like I belong to this neighbourhood.";" The friendships and associations I have with other people in my neighbourhood mean a lot to me."; "I would be willing to work together with others on something to improve my neighbourhood". Response options are ranked on a 5-point Likert scale, from 1= Strongly agree to 5= Strongly disagree. The index provided by UKHLS is computed as the mean reverse-coded response to the original variables, with a final score ranging from 1 to 5, with higher scores indicating greater perceived neighbourhood cohesion. The items showed high internal consistency (Cronbach's Alpha[2] is 0.88). In our dataset, neighbourhood cohesion index is measured in 2018. We decide to centre this variable on the mean, so that regression coefficients can be interpreted as change in loneliness for standard deviation increases in perceived neighbourhood cohesion (see Robinette et al. (2021); O'Donnell et al. (2022)).

Finally, regarding social relations, we focus on two variables measuring network size and mode of communication. Specifically, *TIES* is a dummy variable taking value 1 if number of close ties is greater or equal than 5, 0 otherwise (see Hawkley et al. (2008)); mode of communication is measured by the dummy variable *CHAT*, taking value 1 if time spent chatting with friends on social website is one hour or more on a normal weekday, 0 otherwise (see Kovacs et al. (2021)). The two variables are measured in 2018.

The choice of using the number of close ties to measure the network size comes from the evidence that having more close ties in one's networks is generally associated with lower levels of loneliness (Hawkley & Cacioppo (2010); van Tilburg (1990)). The marginal effect

[1]Buckner (1988) developed an instrument to measure a variable that represents a synthesis of the concepts of psychological sense of community, attraction onto neighbourhood and social interaction within a neighbourhood. This individual level variable is denominated "cohesion" or "sense of community". When this variable is assessed in a random sample of residents in a geographically bounded neighbourhood, the mean value forms a measure of the neighbourhood cohesiveness. The UKHLS Main Survey provides a measure of neighborhood social cohesion adapted from the original one (See UKHLS (2018)

[2]Cronbach's Alpha (Cronbach (1951)) is a statistical indicator. It is a measure of the internal reliability of the items in an index. It is usually used as a measure of the internal consistency of psychometric test items for a sample of surveyed subjects. Good internal consistency is reached with Cronbach's Alpha greater than 8.

of one additional close tie is especially large for the four closest ties, whereas additional friends beyond the first four continue to be associated with lower levels of loneliness but are not as protective (de Jong Gierveld et al. (2006)). Moreover, those with a larger number of close ties reported lower increase in loneliness during COVID-19 than those with lower counts of very close friends (Kovacs et al. (2021)).

As regards technologically mediated communication, the pandemic represents a unique opportunity to study whether these can act as an effective substitute for face-to-face interaction. Early research on older adults suggested that the strength of social contacts, rather than how frequently they engaged with social contacts, was associated with lower loneliness (Krendl & Perry (2020)); this suggests that technologically mediated communications may not have been effective substitute for other forms of social interaction during the pandemic. Going in this direction, a study from the US that we previously mentioned in the introduction (Kovacs et al. (2021)) found that in-person communication was the only mode of communication with very close ties that appeared to be statistically significant and negatively related to loneliness.

Finally, control variables are organized in two categories: sociodemographic and health conditions. Among sociodemographic variables, we included respondent's gender (1 female, 0 male), age, ethnicity, urban dwelling (1 urban, 0 rural), type of household (single household, household with kids, household with 4 or more individuals), respondent's level of education, occupational status, income and volunteering (1 volunteered in previous 12 months, 0 otherwise). With respect to education, three levels were considered: (1) lower education (no qualification or basic qualification; i.e., level 1–2 in the U.K. education system); (2) medium education (level 3 in the U.K. education system or equivalent qualification); and (3) higher education (i.e., level of education 4–7 in the U.K. education system); regarding occupational status, we distinguished 4 categories: employed, unemployed, students, inactive and others. These variables are measured in 2018.

Among health variables, we included an indicator of general health, the self-assessed health (SAH), long term conditions (LTCond) and disabilities. With regards to the first, the following standard self-assessed health status question was asked: "Would you say that in general your health is: 1) Excellent 2) Very good 3) Good 4) Fair 5) Poor". Answers are scored on a scale from 1 (Excellent) to 5 (Poor). Since the answers could not simply be scored (for example as 1, 2, 3, 4, 5) because the true scale will not be equidistant between categories (O'Donnell et al. (2008)) according to previous literature (see, for instance, Balia & Jones (2008); Di Novi (2010); Di Novi (2013)), we dichotomized the multiple-category responses and constructed a binary indicator SAH with a value of 1 if individuals reported that their health was fair or poor, and 0 otherwise (i.e., excellent, very good, or good). Finally, two dichotomous indicators: LTCond (1 suffers from a long term health condition, 0 otherwise) and disabilities (1 has disability, 0 otherwise). While the question about long term health conditions is repeated across all waves, SAH and disability are only surveyed in 2018. We include these three health variables in the analysis because the correlation coefficient does not suggest collinearity issues (ρ SAH-disability= 0.443; ρ SAH-LTCond = 0.288 ; ρ disability-LTCond=0.338). Table 3.1 presents the variables.

3.3.1 Descriptive statistics

Descriptive statistics are shown in Table 3.2. Around one third of respondents declares to feel lonely often or some of the time (32.7%). Average neighbourhood social cohesion is 3.5. with regards to social relations variables, half of the sample reports having five or more close ties (50.5%) and one in five participants declares spending more than one hour on a normal day chatting with friends (19%). Respondents are aged 16 to 94 and average age is 56 (sd 15). 58% of our sample is female; ethnic minorities account for the 8.5% of the sample. As previously discussed, all respondents in our sample live in England. About half the sample has a university degree (51.7%) and the majority of respondents are employed (56.8%). 16% of the sample lives in a single household and about the 21% lives with kids. One in four volunteered in the previous 12 months (25.2%). With regards to general health, a share of 16.5% of the respondents declares poor or fair conditions, whereas one in two respondents suffers from a chronic condition (52.7%) and one in four has a disability (24.8%).

Figure 3.1 shows how *LONE* variable varies over time: in April and May 2020, at the beginning of the pandemic and during the first national lockdown, loneliness levels are substantially in line with those of 2019. Then, *LONE* decreases between May and September 2020, as "Stay at home" orders end and restrictions on social contacts are eased. Interestingly, peaks in loneliness levels are registered in November 2020 and January 2021, concurrently with England second and third lockdown; at this time, those of spring 2020 are largely overcome.

Figure 3.2 to 3.4 explore the time dynamics in loneliness among groups characterized by different levels of social cohesion and social relations. While trends look similar to that in Figure 3.1, these graphs show a clear connection between pre-pandemic social interactions and loneliness, during coronavirus emergency. Specifically, people who experienced stronger neighbourhood support and stronger social relations, also show lower levels of loneliness.

3.4 Results

3.4.1 Estimates from the linear probability model

This chapter examines the impact of pre-pandemic neighbor cohesion and social relations on the levels of loneliness during the whole period of emergency. As we control for pre-pandemic levels of loneliness, the variation in loneliness is solely attributed to the effects of COVID-19 restrictions.

We begin by presenting the results of the Model 1, namely the linear probability model that examines how neighbourhood cohesion affects loneliness (Table 3.3, Column 1). In the discussion of the results, we concentrate on 1) the coefficient of neighbourhood cohesion 2) the coefficients of the time dummies and of their interaction with neighbourhood cohesion (i.e. ,Var*2019, Var*April 2020, …) and 3) the sum between the coefficient of neighbourhood cohesion and the coefficients of the interaction terms. Full model coefficients are reported in Table A7 in the Appendix.

First of all, the level of neighbourhood relations is strongly associated with loneliness. A one standard deviation (0.737) increase in the level of social cohesion is associated with a – 6.3 percentage points (0.737*-0.085) or 19% in percentage terms (0.063/0.327)in the probability of feeling lonely ($p<0.001$). The magnitude of the effect is pretty big. This finding suggests that, in general, greater perceived neighbourhood cohesion plays a protective role against loneliness. Second, during the pandemic, the average level of loneliness increases (time dummies are significant). Third, interestingly, those individuals that are characterized by higher perception of neighbourhood cohesion experience higher increases in loneliness. The interaction term (i.e. *COHESION* interacted with the time dummy) shows a positive and statistically significant coefficient for each wave between

April 2020 and September 2021.

A one standard deviation increase in the level of social cohesion in April 2020 is associated with a +3.3% ($p<0.001$) increase in feelings of loneliness, with respect to 2018. A one standard deviation increase in the level of social cohesion in November 2020, in correspondence with the U.K. second national lockdown, corresponds to a +2.65% ($p<0.001$) increase in loneliness scores, with respect to 2018. Other coefficients are smaller in size, but still significant. A one standard deviation increase in social cohesion in May 2020 is associated with a +2.17% ($p<0.05$) increase in feelings of loneliness, with respect to 2018; +2.63% ($p<0.001$) in June 2020, compared to 2018; +2.64% ($p<0.001$) in July 2020; +1.84% ($p<0.05$) in September 2020; +2.42% ($p<0.001$) in January 2021 ($p<0.001$); + 2.35% ($p<0.001$) in March 2021; +1.59% ($p<0.001$) in September 2021. This suggests that restrictions on movements and social contacts, due to containment measures implemented at various rates, appear to have increased loneliness among people who were experiencing stronger cohesion in their neighbourhood. The coefficient of the interaction term is not significant in 2019, indicating absence of pre-trends.

Fourth, we consider the sum the coefficient of neighbourhood cohesion and the coefficient of the interaction terms, to analyse whether during the pandemic the overall level of loneliness experienced by those with a higher level of perceived neighbourhood social cohesion was larger than for those with a lower level of perceived neighbourhood social cohesion. In other words, we investigate whether the protective role of social cohesion disappears during the pandemic (Figure 3.5). The coefficients resulting from this sum are statistically significant and negatively associated with loneliness, between April 2020 and September 2021. This suggests that loneliness levels are lower among respondents experiencing higher social cohesion, even during coronavirus pandemic. Therefore, the protective role of neighbourhood social cohesion remains in place also during the pandemic.

Afterwards, we consider the association between respondents' social relations and loneliness; we analyse respondents' number of close ties and time spent chatting with friends on social media. We proceed by presenting the results of the regression of *TIES* on loneliness (Table 3.3, Column 2). As before, our discussion focuses on 1) the coefficient of *TIES* 2) the coefficients of the time dummies and of their interaction with *TIES*(i.e. Var*2019, Var* April 2020, ...) and 3) the sum between the coefficient of *TIES*and the coefficients of the interaction terms. The results are the following (for full model coefficients see Table A7 in the Appendix).

First, the number of close friends is strongly associated with loneliness. Respondents with 5 or more close ties are less likely to experience loneliness by -5.8% ($p<0.001$), compared to respondents who can count on less than 5 close friends. This negative relationship between the two variables is in line with the existing literature that documents that having more confidants over few close friends plays a protective role against loneliness (Hawkley et al. (2008); van Tilburg (1990); Kovacs et al. (2021)). Second, as found in the first regression model, the average level of loneliness increases during the pandemic (time dummies are significant). Third, those individuals with a larger network of close friends experienced a reduction in loneliness during the pandemic: the coefficient of the interaction term between close friends and the time dummy is negative and statistically significant in each wave between April 2020 and September 2021. Again, the coefficient of the interaction term is not significant in 2019, indicating absence of pre-trends.

Finally, we consider the sum between the coefficient of the variable *TIES* and the interaction terms, to estimate if the protective role of friends remains in place during the pandemic (Figure 3.6). The coefficients resulting from this sum are negative and statistically significant, between April 2020 and March 2021. Our findings suggest that those with greater number of close friends experience overall a decrease in loneliness levels during the pandemic, compared to their counterparts with a number of close ties lower than 5.

We conclude by presenting the results of the regression of loneliness on *CHAT* (Table 3.3, Column 3). Full model coefficients are reported in Table A7 in the Appendix. According to the table, there is a clear, significant relation between the time spent chatting on social media and feelings of loneliness. Spending 1 or more hours a day chatting on social website increases the probability of feeling lonely by +4.5% ($p<0.001$), with respect to chatting less than 1 hour/day or not chatting at all. Once again it is confirmed that the average level of loneliness increases during the pandemic (time dummies are significant). Interestingly, changes in loneliness scores during the pandemic do not differ by time spent chatting online with friends: the coefficient of the interaction term between the variable and time dummies are never significant. Then, we discuss the sum of the coefficient of the variable and the coefficient of the interaction terms, between 2019 and September 2021

(Figure 3.7). All coefficients are statistically significant with positive sign, highlighting a strong relation between time spent on the social and respondent's feelings of loneliness, both before and during the pandemic.

To conclude the discussion of the variables of interest, we summarize two major findings. First of all, neighbourhood social cohesion is strongly and negatively associated with loneliness; thus, people who perceive greater cohesion at local levels are less likely to experience loneliness in general and experience a decrease in feelings of loneliness during the pandemic. Secondly, with regards to individual's social relations, people who can count on numerous friends are less likely to suffer from loneliness, both in normal times and in period of crisis; whereas, communication with friends via social media does not seem to provide meaningful interactions with a protective role against loneliness. Regarding control variables, our results confirm early research on loneliness during COVID-19, across three regressions (Bu et al. (2020); Groarke et al. (2020)). Loneliness is associated with being female and belonging to ethnic minorities. Age is positively associated with feelings of loneliness, whereas we do not find a significant association with educational attainment. Income appears negatively related with loneliness; living alone and living in a household with kids show a positive association with loneliness. Poor health conditions increase the probability of feeling lonely. Finally, volunteering is negatively related to loneliness.

3.4.2 Estimates from the probit model

Table 3.4 shows the marginal effects of the probit model, i.e. Model 2, describing the association between social cohesion, social relations and loneliness (see Table A8 in the Appendix for full model marginal effects). Results confirm our previous findings: first, there is a negative, significant effect of neighbour cohesion on loneliness (Column 1); second, there exists a negative association between close ties on loneliness (Column 2); third, time spent chatting with friends on social website shows a positive, significant effect on the outcome variable (Column 3). A marginal change in *COHESION* leads to a -5.6% ($p<0.01$) decrease in the probability of feeling lonely (Column 1); having five or more close ties is associated with a -6.2% ($p<0.01$) decrease in the likelihood of feeling lonely, compared to having less than 5 close friends (Column 2). Chatting with friends more than one hour a day leads to a +4.1% increase in the likelihood of loneliness feelings, compared to not chatting or chatting for a shorter period of time a day (Column 3). Finally, there is a major difference from Model 1: the interaction term between TIES and wave dummies (Column 2) shows a positive sign, whereas the linear probability model produced negative coefficients. Thus, respondents with a larger network of relations appear to be more likely to suffer feelings of loneliness throughout the pandemic, compared to those people with a lower number of confidants. We believe that the probit specification, that better suits our model, produces more correct estimates.

3.4.3 Heterogeneity analysis by gender and age

We also conduct heterogeneity analysis to investigate differences in the probability of experiencing loneliness and in the effect of the pandemic by gender and age.

With respect to gender, results indicate that the protective effect of social cohesion and number of close friends is larger for women than for men (Table 3.5, Column 1-4). A one standard deviation increase in social cohesion is associated with a -3.97% decrease in loneliness scores among women (vs -2.34%, $p<0.01$ for men). Figure 3.8 plots the coefficients and the 95% confidence intervals resulting from the sum of *COHESION* and the interaction term between the variable and wave dummies, suggesting that the effect is larger for females compared to males, even during coronavirus pandemic. Having five or more close friends leads to a -7.59% ($p<0.01$) decrease in the likelihood of loneliness among females (vs -3.17%, $p<0.05$ for men). Figure 3.9 plots the coefficients and the 95% confidence intervals resulting from the sum of *TIES* and the interaction term between the variable and wave dummies, suggesting that close friends are protective against loneliness for women, especially at the beginning and at the end of the pandemic period.

Column 5 and 6 in Table 3.5 report the increasing effect of time spent chatting on social media on loneliness, that is almost identical between males and females (males: +5.41%, $p<0.05$, females: +5.48%, $p<0.01$). Figure 3.10 plots coefficients and the 95% confidence intervals resulting from the sum of *CHAT* and the interaction term between the variable and wave dummies, clearly showing the persistence of this positive effect throughout the period analysed.

We then split our sample in five age groups (under 30, 30-45, 46-59, 60-69, 70+) and outline some interesting results (Figure 3.11). First, the effect of *CLOSE* and *CHAT* is largest in the group of young people. Second, *COHESION* is negatively and statistically related to loneliness across all age groups, with the magnitude of the coefficient increasing with age. Third, the association between close friends and loneliness is significant across age groups, although the size of the coefficient and the level of significance decrease with age, which suggests that, among elderly, neighbour social relations play a stronger protective role against loneliness compared to personal relations. Fourth, when we focus on the group of elderly age 70+, *COHESION* is the only statistically significant predictor of loneliness; this suggests that relations at community level are especially important for older people, as their everyday life is particularly bounded to the place where they live.

3.4.4 Sensitivity analysis

We modify our outcome variable LONE, which is now a dummy variable equal to 1 if respondents feel lonely "Often", 0 "Hardly ever, never" and "Some of the time". The new outcome variable sets a higher threshold for feeling lonely compared to the original one, thus restricting the group of people in this category. Table 3.6 shows the estimates of the linear probability model describing the association between social cohesion, social relations and the variable lone in the new specification; results confirm previous findings, for all variables of interest. First, a one standard deviation (0.737) increase in the level of social cohesion is associated with a – 2.8% in loneliness scores ($p<0.01$). The sum of the coefficient of the variable and the interaction term, between April 2020 and September 2021, is statistically significant with negative sign, highlighting a strong relation between cohesion and respondent's feelings of loneliness during the pandemic. Second, respondents with five or more close friends experience a decrease in loneliness by -2.4% ($p<0.01$), compared to those who can count on less than 5 confidants. This relation is confirmed throughout coronavirus emergency, as the sum of the coefficient and the interaction term is significant with negative sign between April and September 2021. Third, chatting with friends one hour or more a day is associated with a +2.3% in loneliness scores ($p<0.05$).

3.5 Conclusions and policy implications

COVID-19 pandemic has led to the implementation of unprecedented social distancing measures that significantly restricted social life. Despite effectiveness in decreasing infections, the reduction and, in some cases, the complete absence of social contacts have been found to be detrimental to individual's wellbeing, i.e., in this contribution the perception of loneliness.

The present study addressed two research questions in the context of the pandemic. First, we analysed the impact of greater perceived neighbourhood social cohesion on loneliness and, second, we assessed the effect of two indicators of people's social networks (i.e., close ties and time spent chatting on social media) on loneliness. We exploit a large representative sample from England, covering the 2018-2021 period. We highlight three major findings. First, neighbourhood social cohesion is strongly associated with lower levels of loneliness before and during the pandemic. Second, individuals with more close ties are less likely to experience loneliness, both before and during the pandemic. Third, communication via social website appears to be positively associated with loneliness before the pandemic. Moreover, neighbour cohesion seems particularly important for the elderly, who are less likely to experience loneliness when they experience connections at local level. On the other hand, young people benefit especially from a larger network of friends, while communication via social media does not appear to shield from loneliness.

Our findings, by documenting the protective role of social relations against loneliness, point to the importance of fostering and maintaining social connections, even during pandemics. Hence, they call for initiatives that promote cohesion and relations at community. In this sense, social prescribing could represent an interesting approach. Social prescribing is a relatively new concept that addresses social determinants of health by promoting community and voluntary sector engagement and providing tailored support to individuals (South et al. (2008)). This approach involves non-medical interventions proposed by GPs to address wider determinants of health and improve health behaviors (South et al. (2008); Bickerdike et al. (2017); Drinkwater et al. (2019)). It targets those who require greater social and emotional support and has been found to improve wellbeing, physical health, and reduce social isolation and loneliness. Implementing social prescribing initiatives during adversities may help individuals develop personal resources to ward off loneliness and build strong communities for future shocks (see Robinette et al. (2021)).

To our knowledge, this is the first study to establish an association between neighbourhood cohesion, social relations and loneliness during 2020 coronavirus pandemic, in England, but is not without limitations. First, our analysis is missing geographical identifiers at community level, hence, we were not able to cluster individuals at local level to run multilevel models, which would have better suited our analysis. Further research should include such factors in the analysis, depending on data availability. Second, neighbourhood cohesion is measured by the participant's subjective perceptions, rather than an objective measure. The way individuals perceive their neighbourhoods can have a significant impact on their feelings of loneliness. This is consistent with research on subjective well-being, which indicates that people's experiences of their lives differ from objective measures of well-being such as income, and that these experiences can predict life outcomes in a unique way (Diener et al. (2020)). Further research ought to consider how perceived social relations relate to and interact with objective and externally measured indicators (e.g., deprivation rates provided by the U.K. Census) to buffer loneliness levels during crises. Finally, further research should explore how informal helping behaviours (e.g., shopping for others, helping others with basic needs) which became common throughout the pandemic might have affected loneliness feelings, for both providers and receivers of help.

Figures

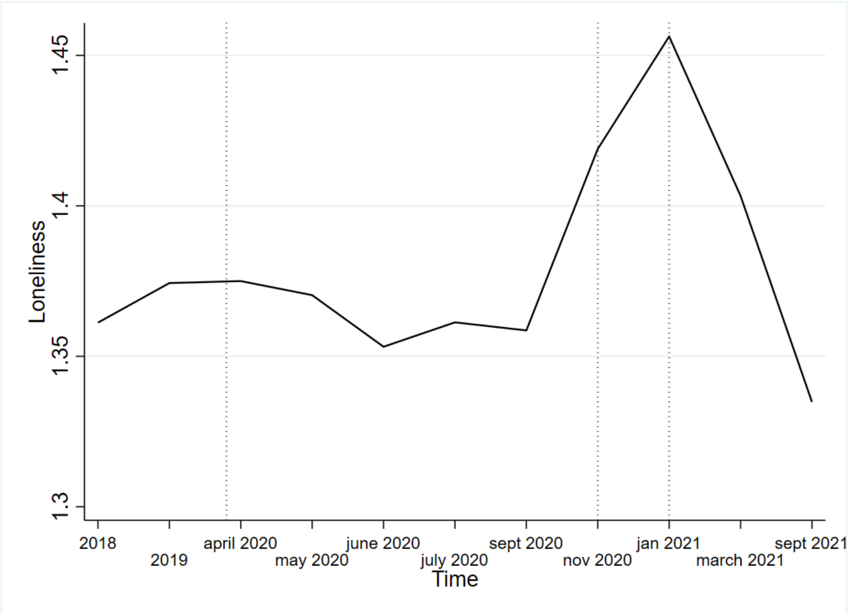

Figure 3.1: Loneliness over time

Note: this figure reports the evolution of the variable *LONE* over time, between 2018 and September 2021. Dash vertical lines represent the beginning dates of the first, second and third lockdown in England, respectively.

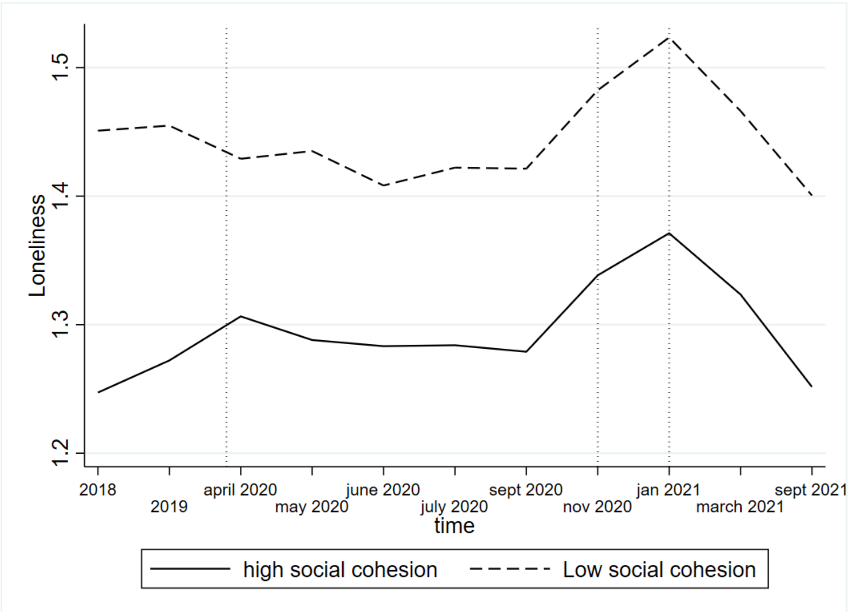

Figure 3.2: Loneliness over time by social cohesion levels

Note: this figure reports the evolution of the variable *LONE* by social cohesion levels over time, between 2018 and September 2021. Dash vertical lines represent the beginning dates of the first, second and third lockdown in England, respectively.

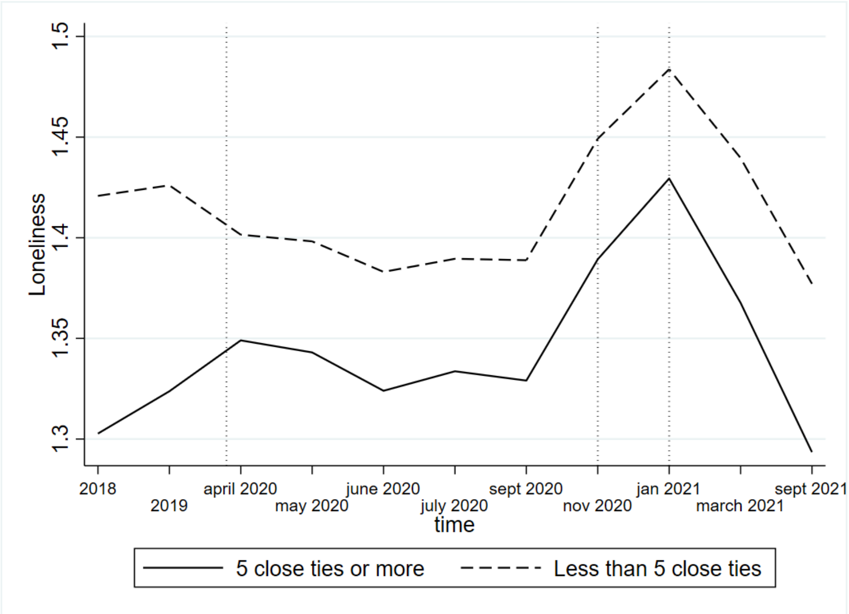

Figure 3.3: Loneliness over time by number of close friends

Note: this figure reports the evolution of the variable *LONE* by number of close friends over time, between 2018 and September 2021. Dash vertical lines represent the beginning dates of the first, second and third lockdown in England, respectively.

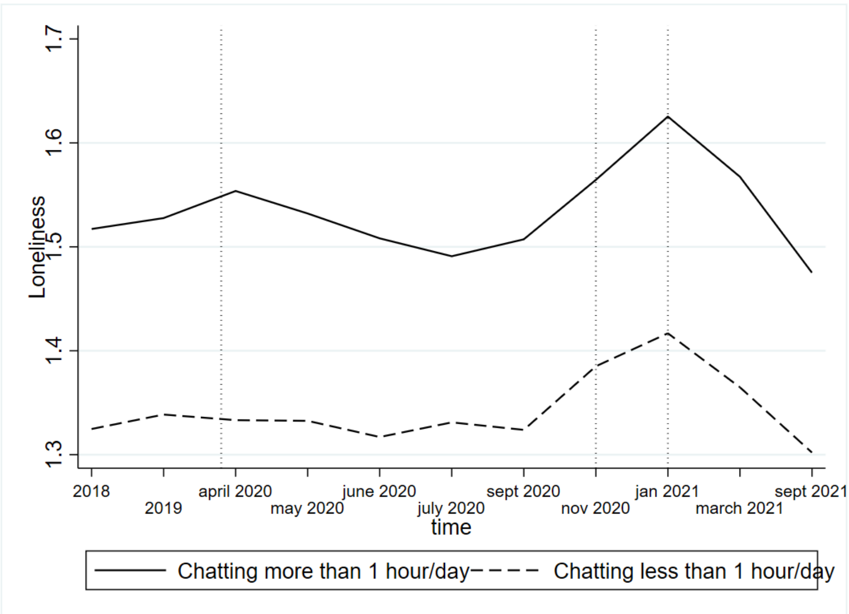

Figure 3.4: Loneliness over time by time spent chatting on social website

Note: this figure reports the evolution of the variable *LONE* by hours spent chatting on social website over time, between 2018 and September 2021. Dash vertical lines represent the beginning dates of the first, second and third lockdown in England, respectively.

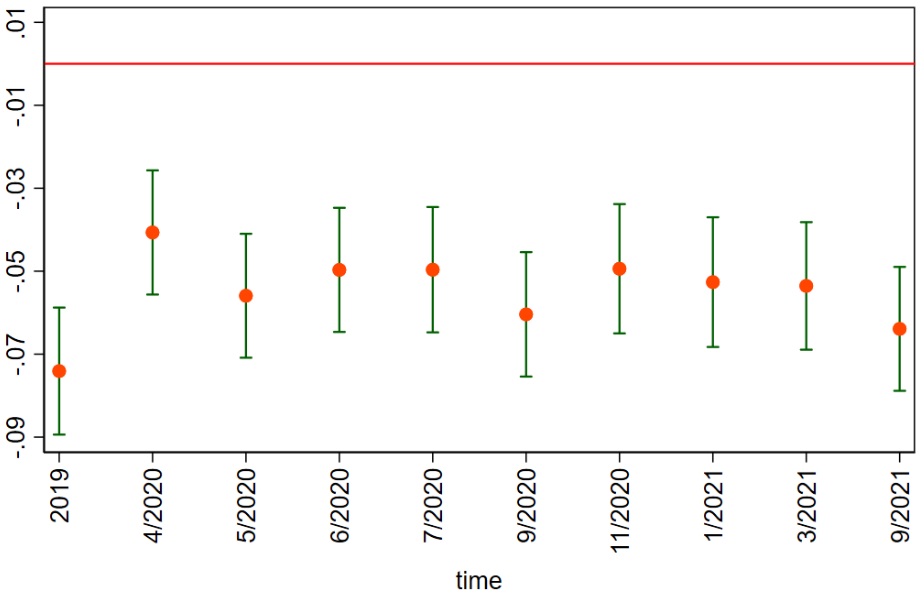

Figure 3.5: Coefficients of *COHESION*

Note:the figure reports the coefficients of the variable *COHESION* and the 95% confidence intervals resulting from the sum between the variable and the interaction between cohesion and the wave dummies (Model 1 of Equation 2), leaving Wave 1 of Covid-19 Survey (Late April) as base category.

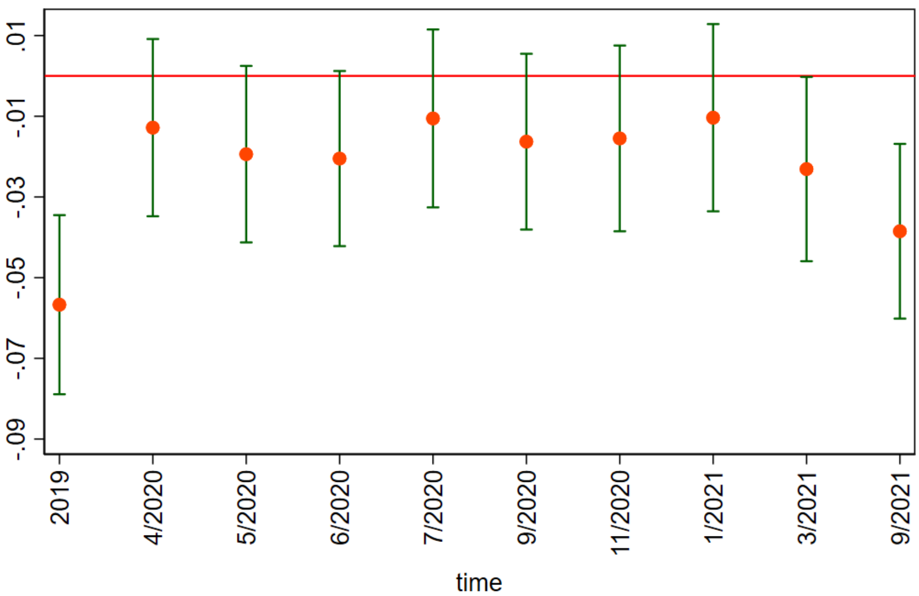

Figure 3.6: Coefficients of *TIES*

Note: the figure reports the coefficients of the variable *TIES* and the 95% confidence intervals resulting from the sum between the variable and the interaction between cohesion and the wave dummies (Model 1 of Equation 2), leavingWave 1 of Covid-19 Survey (Late April) as base category.

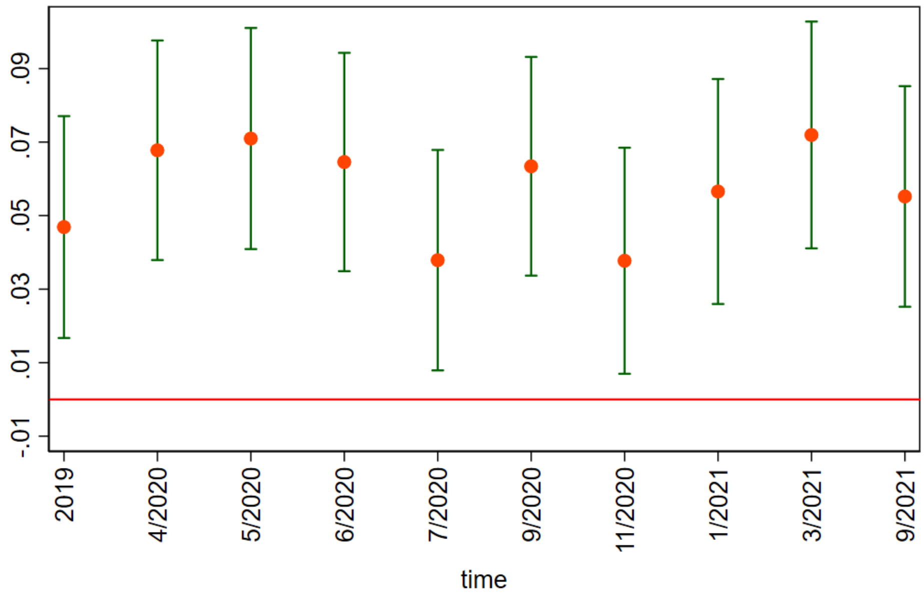

Figure 3.7: Coefficients of *CHAT*

Note: the figure reports the coefficients of the variable *CHAT* and the 95% confidence intervals resulting from the sum between the variable and the interaction between cohesion and the wave dummies (Model 1 of Equation 2), leaving Wave 1 of Covid-19 Survey (Late April) as base category.

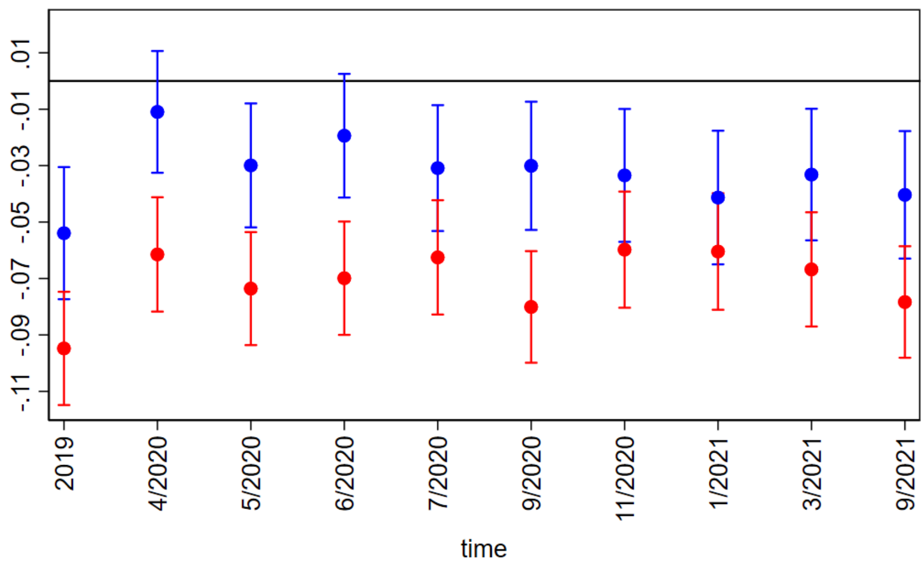

Figure 3.8: Heterogeneity analysis by gender - *COHESION*

Note: the figure reports the coefficients and the 95% confidence intervals of the variable *COHESION* from the linear probability model describing the association between this variables and *LONE*, by gender. Estimates for males are in blue, for females in red.

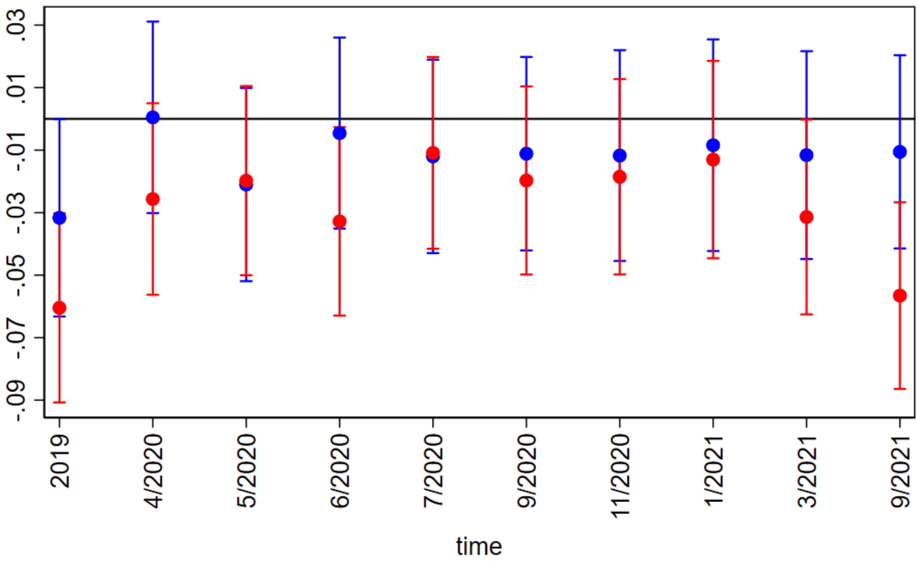

Figure 3.9: Heterogeneity analysis by gender - *TIES*

Note: the figure reports the coefficients and the 95% confidence intervals of the variable *TIES* from the linear probability model describing the association between this variables and *LONE*, by gender. Estimates for males are in blue, for females in red.

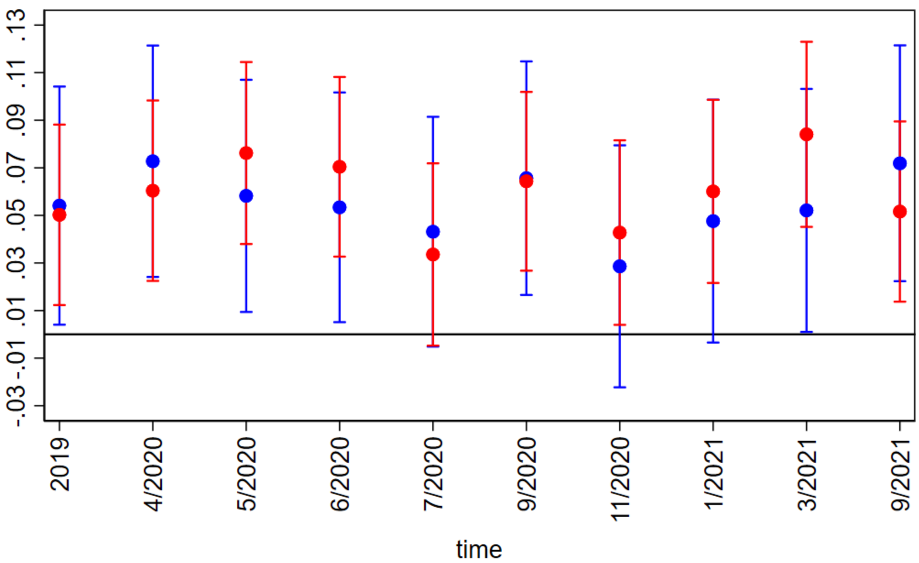

Figure 3.10: Heterogeneity analysis by gender - *CHAT*

Note: the figure reports the coefficients and the 95% confidence intervals of the variable *CHAT* from the linear probability model describing the association between this variables and *LONE*, by gender. Estimates for males are in blue, for females in red.

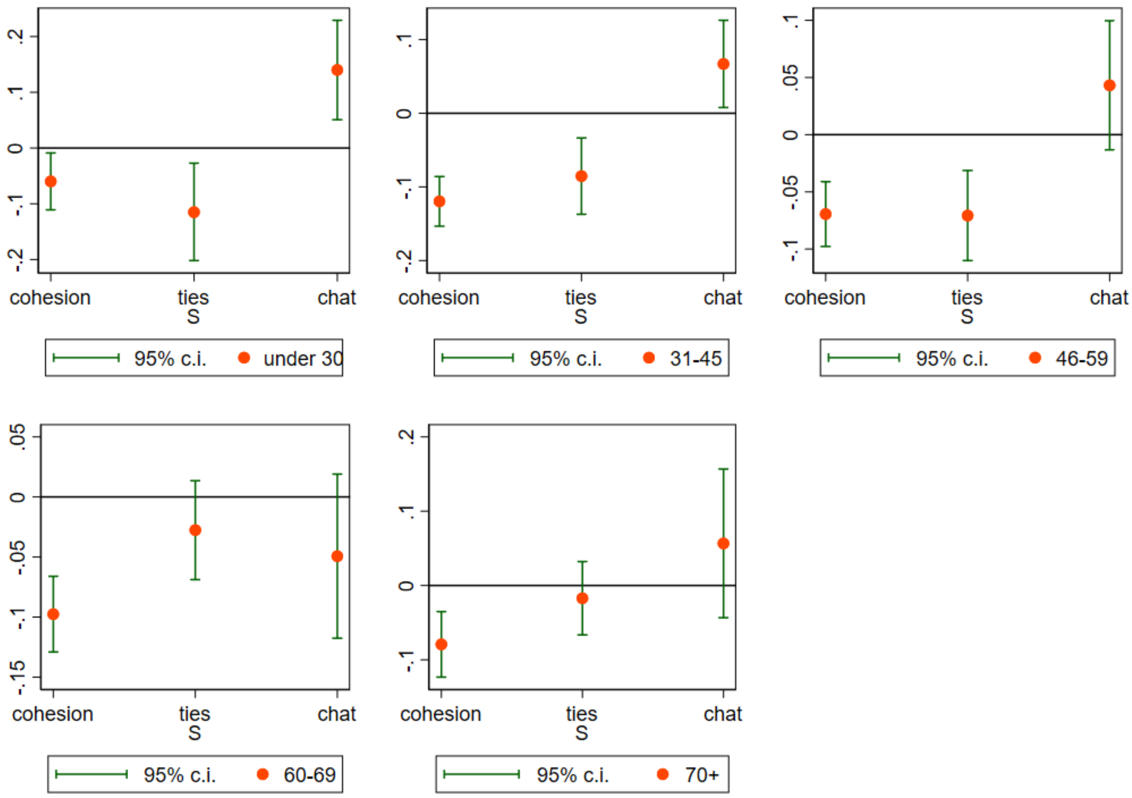

Figure 3.11: Heterogeneity analysis by age class

Note: the figure reports the coefficients and the 95% confidence intervals of the variables *COHESION, TIES, CHAT* from the linear probability model describing the association between these variables and loneliness, by age groups.

Tables

Table 3.1: Variables names and definition

Variable name	Description	Survey (S.) & Wave (W)
LONE	Dummy 1 if feeling lonely “Often” or “Sometimes”, 0 if feeling lonely “Hardly ever, never”	Main S. W9,10 & Covid S. W1-9
COHESION	Continous, higher values stand for higher cohesion	Main S. W9
TIES	Dummy 1 if number of close ties is greater or equal than 5, 0 otherwise	Main S. W9
CHAT	Dummy 1 if respondent spends 1+ hours/day chatting with friends on social media, 0 otherwise	Main S. W9
FEMALE	Dummy 1 if Female, 0 Male	Main S. W9,10 & Covid S. W1-9
AGE	Discrete	Main S. W9,10 & Covid S. W1-9
NONWHITE	Dummy 1 if non white, 0 otherwise	Main S. W9
LOWEREDU	Dummy 1 if level of completed education is: GCSE or below, 0 otherwise	Main S. W9
MEDIUMEDU	Dummy 1 if level of completed education is: A-levels or equivalent, 0 otherwise	Main S. W9
HIGHEREDU	Dummy 1 if level of completed education is: Degree or above, 0 otherwise	Main S. W9
EMPLOYED	Dummy 1 if employed, 0 otherwise	Main S. W9
UNEMPLOYED	Dummy 1 if unemployed, 0 otherwise	Main S. W9
STUDENT	Dummy 1 if student, 0 otherwise	Main S. W9
INACTIVE	Dummy 1 if inactive and other, 0 otherwise	Main S. W9
HHSINGLE	Dummy 1 if single household, 0 otherwise	Main S. W9,10 & Covid S. W1-9
HHCHILDREN	Dummy 1 if children in household, 0 otherwise	Main S. W9,10 & Covid S. W1-9
HH4+	Dummy 1 if 4+ people in household, 0 otherwise	Main S. W9,10 & Covid S. W1-9
URBAN	Dummy 1 if living in urban area, 0 if rural	Main S. W9
INCOME	Continuous	Main S. W9
VOLUNTEER	Dummy 1 if respondent volunteered in the last 12 months, 0 otherwise	Main S. W9
SAH	1 if SAH is fair or poor, 0 otherwise	Main S. W9
LTCOND	Dummy 1 if respondent suffers from a long term health condition , 0 otherwise	Main S. W9,10 & Covid S. W1-9
DISABILITY	Dummy 1 if respondent has disability, 0 otherwise	Main S. W9

Table 3.2: Descriptive statistics

	Mean	Sd	Min	Max
LONE	0.327	0.469	0	1
COHESION	0.006	0.737	-2.518	1.481
TIES	50.55	0.500	0	1
CHAT	0.189	0.392	0	1
FEMALE	0.583	0.493	0	1
NONWHITE	0.085	0.279	0	1
AGE	56.191	15.136	16	94
LOWEREDU	0.288	0.453	0	1
MEDIUMEDU	0.188	0.391	0	1
HIGHEREDU	0.517	0.500	0	1
EMPLOYED	0.568	0.495	0	1
UNEMPLOYED	0.017	0.130	0	1
STUDENT	0.020	0.139	0	1
INACTIVE	0.394	0.489	0	1
URBAN	0.752	0.432	0	1
HHSINGLE	0.161	0.367	0	1
HHCHILDREN	0.215	0.411	0	1
HH4+	0.084	0.278	0	1
INCOME	2196.462	1827.422	0	21785.41
VOLUNTEER	0.252	0.434	0	1
SAH	0.165	0.371	0	1
LTCOND	0.527	0.499	0	1
DISABILITY	0.248	0.432	0	1

For all variables, 64,248 observations are available

Table 3.3: Estimates of the linear probability model

	Dependent variable: LONE		
	Social factor included as independent variable		
	(1)	(2)	(3)
	COHESION	*TIES*	*CHAT*
S	-0.085***	-0.058***	0.045***
	(0.008)	(0.011)	(0.015)
S*2019	0.011	-0.002	0.002
	(0.011)	(0.016)	(0.021)
S*April 2020	0.045***	-0.046***	0.023
	(0.011)	(0.016)	(0.021)
S*May 2020	0.029***	-0.039**	0.026
	(0.011)	(0.016)	(0.021)
S*June 2020	0.036***	-0.038**	0.020
	(0.011)	(0.016)	(0.021)
S*July 2020	0.036***	-0.048***	-0.007
	(0.011)	(0.016)	(0.021)
S*Sept 2020	0.025**	-0.042***	0.019
	(0.011)	(0.016)	(0.021)
S*Nov 2020	0.036***	-0.043***	-0.007
	(0.011)	(0.016)	(0.022)
S*Jan 2021	0.033***	-0.048***	0.012
	(0.011)	(0.016)	(0.022)
S*March 2021	0.032***	-0.035**	0.027
	(0.011)	(0.016)	(0.022)
S*Sept 2021	0.022**	-0.020	0.011
	(0.011)	(0.016)	(0.021)
Time effect	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	64,248	64,248	64,248
R-squared	0.155	0.155	0.155

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Note: Each column reports results from a different regression. In all columns (1) to (3) the dependent variable is the probability of feeling lonely "Often" or "Some of the time". In each regression, we consider one variable at a time among *COHESION*, *TIES*, *CHAT*, plus time trends and the interaction between the variable and time dummies. Baseline category is year 2018.

Table 3.4: Estimates of the probit model

	Dependent variable: LONE		
	Social factor included as independent variable		
	(1)	(2)	(3)
	COHESION	*TIES*	*CHAT*
S	-0.055***	-0.026***	0.050***
	(0.002)	(0.003)	(0.005)
S *2019	0.011	0.001	0.001
S *april 2020	0.042***	0.045***	0.020
S *may 2020	0.027***	0.038**	0.023
S *june 2020	0.034***	0.037**	0.018
S *july 2020	0.034***	0.047***	-0.008
S*sept 2020	0.023**	0.041***	0.017
S*nov 2020	0.035***	0.043***	-0.012
S *jan 2021	0.033***	0.049***	0.004
S *march 2021	0.031***	0.036**	0.021
S *sept 2021	0.019*	0.018	0.011
Time effect	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	64,248	64,248	64,248

*** p<0.01, ** p<0.05, * p<0.1 Note: Each column reports marginal effects from a different regression. In all columns (1) to (3) the dependent variable is the probability of feeling lonely "Often" or "Some of the time". In each regression, we consider one variable at a time among *COHESION*, *TIES*, *CHAT*, plus time trends and the interaction between the variable and time dummies. Baseline category is year 2018. The coefficient S (Columns 1-3) is the average marginal effect of the corresponding social factor variable. The coefficients S*Wave dummies (Columns 1-3) are the average marginal effect of S computed at each specific value of the Wave dummies.

Table 3.5: Heterogeneity analysis by gender

	Dependent variable: LONE					
	Social factor included as independent variable					
	(1)		(2)		(3)	
	COHESION		*TIES*		*CHAT*	
	M	F	M	F	M	F
S	-0.054***	-0.105***	-0.032**	-0.076***	0.054**	0.044**
	(0.012)	(0.01)	(0.016)	(0.015)	(0.025	(0.008)
S*2019	0.043***	0.044***	-0.032	-0.050**	0.019	0.016
	(0.016)	(0.014)	(0.022)	(0.022)	(0.035)	(0.027)
S*April 2020	0.024	0.032**	-0.011	-0.056***	0.004	0.032
	(0.016)	(0.014)	(0.022)	(0.021)	(0.035)	(0.027)
S*May 2020	0.034**	0.035**	-0.027	-0.043**	-0.001	0.026
	(0.016)	(0.014)	(0.022)	(0.021)	(0.035)	(0.027)
S*June 2020	0.023	0.043***	-0.019	-0.065***	-0.011	-0.011
	(0.016)	(0.014)	(0.022)	(0.022)	(0.035)	(0.027)
S*July 2020	0.024	0.025*	-0.020	-0.056***	0.011	0.02
	(0.016)	(0.014)	(0.022)	(0.021)	(0.035)	(0.027)
S*Sept 2020	0.020	0.045***	-0.02	-0.057***	-0.025	-0.002
	(0.017)	(0.014)	(0.023)	(0.021)	(0.036)	(0.027)
S*Nov 2020	0.013	0.045***	-0.023	-0.062***	-0.006	0.015
	(0.016)	(0.014)	(0.02)4	(0.022)	(0.036)	(0.027)
S*Jan 2021	0.021	0.0385***	-0.020	-0.044**	-0.002	0.039
	(0.016)	(0.014)	(0.023)	(0.022)	(0.036)	(0.027)
S*March 2021	0.013	0.027*	-0.021	-0.019	0.018	0.007
Time effects	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes
Obs	24,385	37,428	24,385	37,428	24,385	37,428

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Note: Each column reports results from a different regression. In all columns (1) to (6) the dependent variable is the probability of feeling lonely "Often" or "Some of the time", with base category feeling lonely "Hardly ever, never". In each regression, we consider one variable at a time among *COHESION* (columns 1-2), *TIES* (columns 3-4) and *CHAT* (columns 5-6), plus time trends and the interaction between the variable and time dummies; moreover, the regression is run separately for males and females. Baseline category is year 2018.

Table 3.6: Sensitivity analysis. Estimates of LPM with new specification of the outcome variable

	Dependent variable: LONE		
	Social factor included as independent variable		
	(1)	(2)	(3)
	COHESION	*TIES*	*CHAT*
S	-0.038***	-0.024***	0.023**
	(0.005)	(0.006)	(0.009)
S*2019	0.008	0.014*	-0.009
	(0.007)	(0.008)	(0.013)
S*April 2020	0.015**	0.021**	0.011
	(0.007)	(0.008)	(0.013)
S*May 2020	0.017**	0.022***	-0.012
	(0.007)	(0.008)	(0.013)
S*June 2020	0.022***	0.020**	-0.012
	(0.007)	(0.008)	(0.012)
S*July 2020	0.020***	0.015*	-0.017
	(0.007)	(0.008)	(0.012)
S*Sept 2020	0.019***	0.018**	-0.022*
	(0.007)	(0.008)	(0.012)
S*Nov 2020	0.013*	0.017**	0.003
	(0.007)	(0.008)	(0.013)
S*Jan 2021	0.014*	0.017**	0.011
	(0.007)	(0.009)	(0.014)
S*March 2021	0.017**	0.013	-0.006
	(0.007)	(0.008)	(0.013)
S*Sept 2021	0.023***	0.014*	-0.019
	(0.007)	(0.008)	(0.012)
Time effect	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	64,248	64,248	64,248

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Note: Each column reports results from a different regression. In all columns (1) to (3) the dependent variable is the probability of feeling lonely "Often", with base category feeling lonely "Some of the time" or "Hardly ever, never". In each regression, we consider one variable at a time among *COHESION*, *TIES*, and *CHAT*, plus time trends and the interaction between the variable and time dummies. Baseline category is year 2018.

Appendix

1. An IV strategy for variable *CHAT*

In this Appendix, an IV approach for variable *CHAT* is presented. As this is not the final version of the article, IV strategies for variables *COHESION* and *TIES* are not yet discussed. As previously said in Subsection 2, the identification of the model requests further attention. The three independent variables of interest, i.e. *COHESION*, *TIES* and *CHAT* may be endogenous, since it might be the case that some unobservable variables not included in the model influence these indicators and the outcome variable *LONE* simultaneously. If measuring these three variables in 2017-2018, prior to the outcome variable, excluded the issue of reverse causality, a different strategy is needed to address the endogeneity bias. Two instrumental variables for *CHAT* are considered, i.e. broadband connection (*PCBROAD*) and belonging to social network (*SOCWEB*).

A1. Broadband connection

Understanding Society Main Survey provides information on broadband connection at household level in Wave 7, fieldwork 2015-2016. The question asks to households: "Do you have a broadband connection?", with possible answers "1. Yes; 2. No; 3. I do not know". The question is exclusively posed to households having access to the internet from home. Those that do not have internet access count as inapplicable respondents. The information on broadband connection is prior to that of variable *CHAT*, which is included in UKHLS Wave 9, fieldwork 2017-2018.

I am going to discuss whether having broadband connection at home may work as instrumental variable for variable *CHAT*. I construct a new dummy variable called (*PCBROAD*) taking value 1 if household has broadband connection, 0 otherwise (i.e. either the household does not have broadband connection, or the household does not know, or the household was not asked this question). My hypothesis is that broadband connection is an exogenous factor; is it correlated with time spent chatting with friends on social media, while it is not correlated with outcome variable *LONE*. The only way in which broadband connection affects feelings of loneliness is through variable *CHAT*.

Table A1 provides correlation matrix between variable (*PCBROAD*) and *CHAT*, with p-values. The correlation coefficient is very small in size, suggesting a weak connection between the candidate instrument and the endogenous regressor, though it is statistically significant. The negative sign may be explained by the fact that the use of broadband connection is likely to affect the most working with big files of data, making videocalls or watching movies, rather than chatting with friends on social web-sites.

Then, IV regression is performed with Stata command ivreg2. The interaction term *CHAT**Wave dummies contains the endogenous variable so it has to be instrumented. Table A2, Column 1 provides the first stage regression coefficients: the endogenous variable *CHAT* is regressed on (*PCBROAD*), the interaction term between *PCBROAD* and time dummies, and other controls. The coefficient of the candidate instrument is not significant and the F-test is low, thus, having broadband connection should not be considered as an instrument for variable *CHAT*.

Table A1. Correlation matrix between variables *PCBROAD* and *CHAT*

	CHAT	PCBROAD
CHAT	1	
PCBROAD	-0.067***	1

*** $p<0.01$

A2. Belonging to social network web-sites

Understanding Society Main Survey provides information on social web-sites membership at individual level in Wave 9, fieldwork 2017-2018. The question asks to respondents: "Do you belong to any social networking web-sites?", with possible answers "1. Yes, 2. No.". No other information is provided on the kind of social network web-sites the question refers to. This information is registered in the same wave of interview as variable *CHAT*, with main difference that the question on time spent chatting with friends is only asked to members of online social networks. I construct variable *SOCWEB* taking value 1 if respondent belongs to any social website, 0 otherwise (i.e., respondent does not belong to any of it).

I am going to discuss whether variable *SOCWEB* may work as instrumental variable for *CHAT*. My hypothesis is that belonging to a social network is strongly correlated with time spent chatting with friends, while it does not directly influences feelings of loneliness. Nowadays, social web-sites are a pervasive phenomenon, with thousands of enrolled members all over the world, not only among the young; having an account on any social web-sites is almost as common as having a mobile phone. Therefore, I hypothesize that there is not a direct connection between social network membership and loneliness, unless through time spent chatting with friends on these web-sites.

Table A4 provides correlation between variable *SOCWEB* and *CHAT*, with p-values. The correlation is statistically significant, with magnitude of the coefficient 37.5% and positive sign, suggesting a strong, direct relation between belonging to a social network and time spent chatting with friends, as it is clearly reasonable. Then, I perform IV regression with Stata command ivreg2.

Table A2, Column 2 provides the first stage coefficients, coming from the regression of *CHAT* on instrumental variable *SOCWEB*, on the new interaction term generated as *SOCWEB**Wave dummies and other exogenous covariates. The coefficient of the instrumental variable appears statistically significant with positive sign, suggesting a strong relation between social website membership and time spent chatting with friends. The F-test shows a high coefficient, thus supporting *SOCWEB* as candidate instrument for variable *CHAT*.

Table A3 provides the second stage regression coefficients, i.e. the estimates coming from regressing outcome variable *LONE* on the instrumented variable *CHAT*, instrumented interaction term *CHAT**Wave dummies plus other social relation variables and covariates. While the instrumented variable *CHAT* is not significant, the instrumented interaction term is significant, suggesting a strong, positive effect of chatting with friends on loneliness levels, during the pandemic. In conclusion, the variable *SOCWEB* seems to be an appropriate instrumental variable for *CHAT*, though further analysis is needed to improve the second stage regression.

Table A4. Correlation matrix between variables *SOCWEB* and *CHAT*

	CHAT	SOCWEB
CHAT	1	
SOCWEB	0.375***	1

*** $p<0.01$

Table A2. First stage regression coefficients

Dependent variable: CHAT		
Instrumental variables		
	(1)	(2)
	pcbroad	*socweb*
instrument (I)	0.004	0.233***
	(0.008)	(0.007)
I#2019	0.009	0.005
	(0.007)	(0.010)
I#april 2020	0.016**	0.011
	(0.007)	(0.010)
I#may 2020	0.017**	0.011
	(0.007)	(0.010)
I#june 2020	0.017**	0.011
	(0.007)	(0.010)
I#july 2020	0.018**	0.012
	(0.007)	(0.010)
I#sept 2020	0.020***	0.013
	(0.007)	(0.010)
I#nov 2020	0.021***	0.013
	(0.007)	(0.010)
I#jan 2021	0.022***	0.014
	(0.007)	(0.010)
I#march 2021	0.024***	0.016
	(0.007)	(0.010)
I#sept 2021	0.028***	0.018*
	0.007	0.010
Controls	YES	YES
Wave dummies	YES	YES
N	64248	64248
F test	2.95	833.57

Robust standard errors in parentheses.$***p < 0.01, **p < 0.05, *p < 0.1$

Table A3. Second stage regression coefficients

Dependent variable: LONE	
Instrumental variable	
	(1)
	socweb
CHAT	-0.686
	(0.423)
CHAT#2019	0.159***
	(0.055)
CHAT#april 2020	0.207***
	(0.062)
CHAT#may 2020	0.160**
	(0.063)
CHAT#june 2020	0.114*
	(0.064)
CHAT#july 2020	0.183***
	(0.064)
CHAT#sep 2020	0.149**
	(0.067)
CHAT#nov 2020	0.448***
	(0.068)
CHAT#jan 2021	0.595***
	(0.069)
CHAT#mar 2021	0.410***
	(0.072)
CHAT#sep 2021	0.068
	(0.079)
Control	YES
Wave dummies	YES
N	64248

Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

2. Extended tables

Table A7. Full model coefficients from the linear probability model presented in Table 3.3

	Dependent variable: LONE		
	Social factor included as independent variable		
	(1)	(2)	(3)
	COHESION	*TIES*	*CHAT*
COHESION	-0.085***	-0.058***	-0.058***
	(0.008)	(0.003)	(0.003)
TIES	-0.026***	-0.058***	-0.026***
	(0.003)	(0.011)	(0.003)
CHAT	0.056***	0.056***	0.045***
	(0.005)	(0.005)	(0.015)
FEMALE	0.092***	0.092***	0.092***
	(0.004)	(0.004)	(0.004)
AGE	-0.006***	-0.006***	-0.006***
	(0.000)	(0.000)	(0.000)
NONWHITE	0.041***	0.041***	0.041***
	(0.007)	(0.007)	(0.007)
LOWEDU	0.007	0.007	0.007
	(0.005)	(0.005)	(0.005)
HIGHEREDU	0.004	0.004	0.004
	(0.005)	(0.005)	(0.005)
UNEMPLOYED	0.009	0.009	0.009
	(0.014)	(0.014)	(0.014)
STUDENT	-0.010	-0.011	-0.011
	(0.015)	(0.015)	(0.015)
INACTIVE	0.019***	0.019***	0.019***
	(0.005)	(0.005)	(0.005)
URBAN	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.004)
INCOME	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
HHSINGLE	0.254***	0.255***	0.255***
	(0.005)	(0.005)	(0.005)
HHCHILDREN	0.011**	0.011**	0.011**
	(0.005)	(0.005)	(0.005)
HH4+	-0.008	-0.007	-0.006
	(0.007)	(0.007)	(0.007)
SAH	0.153***	0.153***	0.152***
	(0.006)	(0.006)	(0.006)
LTCOND	0.039***	0.039***	0.040***
	(0.004)	(0.004)	(0.004)
DISABILITY	0.089***	0.089***	0.089***
	(0.005)	(0.005)	(0.005)
VOLUNTEER	-0.007*	-0.007*	-0.007*
	(0.004)	(0.004)	(0.004)

Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

Table A7 continues.

	(1) *COHESION*	(2) *TIES*	(3) *CHAT*
2019	0.023***	0.023*	0.023***
	(0.008)	(0.012)	(0.009)
april 2020	0.029***	0.006	0.025***
	(0.008)	(0.011)	(0.009)
may 2020	0.019**	-0.000	0.014*
	(0.008)	(0.011)	(0.009)
june 2020	0.011	-0.008	0.007
	(0.008)	(0.011)	(0.009)
july 2020	0.022***	-0.002	0.023***
	(0.008)	(0.012)	(0.009)
sept 2020	0.017**	-0.005	0.013
	(0.008)	(0.011)	(0.009)
nov 2020	0.069***	0.047***	0.070***
	(0.008)	(0.012)	(0.009)
jan 2021	0.096***	0.072***	0.094***
	(0.008)	(0.012)	(0.009)
march 2021	0.061***	0.044***	0.056***
	(0.008)	(0.012)	(0.009)
sept 2021	-0.002	-0.012	-0.004
	(0.008)	(0.012)	(0.009)
S*2019	0.011	0.002	0.002
	(0.011)	(0.016)	(0.021)
S*april 2020	0.045***	0.046***	0.023
	(0.011)	(0.016)	(0.021)
S*may 2020	0.029***	0.039**	0.026
	(0.011)	(0.016)	(0.021)
S*june 2020	0.036***	0.038**	0.020
	(0.011)	(0.016)	(0.021)
S*july 2020	0.036***	0.048***	-0.007
	(0.011)	(0.016)	(0.021)
S*sept 2020	0.025**	0.042***	0.019
	(0.011)	(0.016)	(0.021)
S*nov 2020	0.036***	0.043***	-0.007
	(0.011)	(0.016)	(0.022)
S*jan 2021	0.033***	0.048***	0.012
	(0.011)	(0.016)	(0.022)
S*march 2021	0.032***	0.035**	0.027
	(0.011)	(0.016)	(0.022)
S*sept 2021	0.022**	0.020	0.011
	(0.011)	(0.016)	(0.021)
Constant	0.495***	0.512***	0.497***
	(0.013)	(0.014)	(0.013)
Observations	64,248	64,248	64,248
R-squared	0.155	0.155	0.155

Robust standard errors in parentheses.$***p < 0.01, **p < 0.05, *p < 0.1$

Table A8. Full marginal effects from the probit model presented in Table 3.4

	Dependent variable: LONE Social factor included as independent variable		
	(1)	(2)	(3)
	COHESION	*TIES*	*CHAT*
COHESION	-0.055***	-0.055***	-0.055***
	(0.002)	(0.002)	(0.002)
TIES	-0.026***	-0.026***	-0.026***
	(0.003)	(0.003)	-0.003
CHAT	0.049***	0.049***	0.050***
	(0.004)	-0.004	(0.005)
FEMALE	0.093***	0.093***	0.093***
	(0.004)	-0.004	-0.004
AGE	-0.006***	-0.006***	-0.006***
	(0.000)	0	0
NONWHITE	0.039***	0.039***	0.039***
	(0.006)	-0.006	-0.006
LOWEDU	0.007	0.007	0.007
	(0.005)	-0.005	-0.005
HIGHEREDU	0.005	0.005	0.005
	(0.005)	-0.005	-0.005
UNEMPLOYED	0.002	0.002	0.002
	(0.013)	-0.013	-0.013
STUDENT	-0.025**	-0.025**	-0.025**
	(0.012)	-0.012	-0.012
INACTIVE	0.009*	0.009*	0.009*
	(0.005)	-0.005	-0.005
URBAN	-0.000	0	0
	(0.004)	-0.004	-0.004
INCOME	-0.000***	-0.000***	-0.000***
	(0.000)	0	0
HHSINGLE	0.234***	0.234***	0.234***
	(0.004)	-0.004	-0.004
HHCHILDREN	0.015***	0.015***	0.015***
	(0.005)	-0.005	-0.005
HH4+	-0.006	-0.006	-0.006
	(0.006)	-0.006	-0.006
SAH	0.136***	0.136***	0.136***
	(0.005)	-0.005	-0.005
HEALTH	0.038***	0.038***	0.038***
	(0.004)	-0.004	-0.004
DISABILITY	0.086***	0.086***	0.086***
	(0.004)	-0.004	-0.004
VOLUNTEER	-0.009**	-0.009**	-0.009**
	(0.004)	-0.004	-0.004

Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

Table A8 continues

	Dependent variable: LONE		
	Social factor included as independent variable		
	(1)	(2)	(3)
	COHESION	*TIES*	*CHAT*
S *2019	0.011	0.001	0.001
S *april 2020	0.042***	0.045***	0.020
S *may 2020	0.027***	0.038**	0.023
S *june 2020	0.034***	0.037**	0.018
S *july 2020	0.034***	0.047***	-0.008
S*sept 2020	0.023**	0.041***	0.017
S*nov 2020	0.035***	0.043***	-0.012
S *jan 2021	0.033***	0.049***	0.004
S *march 2021	0.031***	0.036**	0.021
S *sept 2021	0.019*	0.018	0.011
2019	0.079***	0.071**	0.076***
	(0.026)	(0.036)	(0.029)
Apr 2020	0.104***	0.022	0.084***
	(0.026)	(0.036)	(0.029)
May 2020	0.069***	-0.001	0.048*
	(0.026)	(0.036)	(0.029)
June 2020	0.043*	-0.024	0.025
	(0.026)	(0.036)	(0.029)
Jul 2020	0.080***	-0.004	0.079***
	(0.026)	(0.036)	(0.029)
Sep 2020	0.060**	-0.013	0.044
	(0.026)	(0.036)	(0.029)
Nov 2020	0.230***	0.150***	0.232***
	(0.026)	(0.036)	(0.029)
Jan 2021	0.309***	0.221***	0.302***
	(0.026)	(0.036)	(0.029)
Mar 2021	0.204***	0.137***	0.186***
	(0.026)	(0.036)	(0.029)
Sep 2021	-0.004	-0.037	-0.017
	(0.026)	(0.036)	(0.030)
Observations	64,248	64,248	64,248

Robust standard errors in parentheses.$***p < 0.01, **p < 0.05, *p < 0.1$

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