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Spend More, Feel Better?

Investigating the impact of social policy expenditure on the severity of individual depressive symptoms throughout Europe

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ABSTRACT

Depression has recently been highlighted across OECD countries as a public health crisis in need of immediate action. Unfortunately, the most popularized public policy solutions focus on individual biomedical or psychosocial interventions. This thesis draws from a theory on economic determinants of mental health to explore if within-country increases in social protection policy expenditure levels over time can affect individuals' depressive symptom outcomes. We use cross-sectional panel data across three rounds of the European Social Survey and state-level social protection expenditure data from the OECD Social Expenditure database for 16 countries across three years (2006/12/14). We operationalize 8 survey questions from the ESS panel data into a depression score for three different sample populations (N's = 30064, 21309, & 91859). We interact the depression score with country-level social protection expenditure data in 14 fixed effects regressions. Results show that increases in the expenditure level of a majority of state-level social policy programs have a small inverse relationship with individuals' depressive symptom outcomes within the countries we have observed. Thus, within-country increases in social protection expenditure levels have a mitigating effect on individual-level depressive symptoms within that country's population.

Keywords: Mental Health, Depressive Symptoms, Social Policy Expenditure, Fixed-Effects Regression Model, European Social Survey

Words: 20,000

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1. Introduction

In OECD countries, depression is a leading cause of disability and ill health, and it has been rising significantly across all populations during and after the recent COVID-19 pandemic (Silva et al., 2016; World Health Organization [WHO], 2023). However, even before the COVID-19 pandemic, mental health was becoming a hot-topic global policy challenge, with UN officials decrying global mental health as a "neglected issue" in 2015, the UN Sustainable Development Goals (SDG's) adding 'Mental Health' into the goals in 2015, and public calls from academic and policy communities across the world emphasizing the need for drastic action to address global mental disorders (Martin, 2018, p. 1; Votruba & Thornicroft, 2016; Patel et al., 2018). Mental health across the world, and specifically in a European context, is being recognized as a sticky and undervalued policy issue, one in which the causes are various and fiercely debated, and solutions are rolled out either "painfully slow" or not at all (Patel et al., 2018, p. 1553).

Mental distress, and specifically depression, are alarming public health issues, on the rise across European country contexts and negatively exacerbated by current world events (Santomauro et al., 2021; Martin, 2018). European governments and policymakers are now tasked with identifying, funding, and facilitating solutions to mental distress, especially major depressive disorder (Patel et al., 2018). Thus, there is a need for policymakers to obtain information on all the types of solutions that may present ways to mitigate occurrences of major depressive disorder and the depressive symptoms that embody it. Without research into all the types of tools, policymakers may have to help mitigate this public health issue, decision-makers may only focus on the most popularized solutions that only follow specific prescriptive ideas for how mental distress can be combated.

This thesis seeks to explore how socioeconomic policymaking impacts a population's mental health, by asking if, and which, specific socio-economic-related public policies enacted across European countries can affect the rate or severity of depressive symptoms in those country's populations. This study focuses on direct social spending in aggregate categories across multiple country contexts, such as overall public spending on family policy programs, to see if these specific social program groups have a mediating effect on depressive symptoms amongst the country population over distinct time periods. Thus we hope to find out if social theories of health, and mental health specifically, can not only provide prescriptive answers to individuals' mental health symptoms but also reveal overlooked interventions to those same symptoms.

1.1 Relevance

This thesis research began by questioning what role welfare programs, social policy, and public policy professionals have in mitigating individual-level depressive symptoms in EU country populations. We began this line of inquiry because, through the 20th and early 21st centuries, mental health has been primarily categorized and understood through psychiatric and psychological perspectives, which can obscure other more important factors determining individual mental health outcomes, such as social and economic factors (Macintyre, 2018; Fisher & Baum, 2010). However, in the past two decades, multiple studies have begun to point out a clear link between socioeconomic conditions and the mental health outcomes of individuals (Lynch, 2017; Fridelly, 2016, as cited in Ribanszki et al., 2022). With new findings in this realm of socio-economic impacted mental health research, it is becoming clear that "common mental disorders, such as depression, are sensitive to the social, political, and economic environments in which people live" and that there is a link connecting economic inequality and poor mental health outcomes (Niedzwiedz et al., 2016, p. 1005; Macintyre, 2018; Fisher & Baum, 2010).

However, even in the light of recent findings regarding the socio-economic impacts on individual mental health, many interventions to combat mental disorders across global communities are psychosocial interventions, or biomedically focused interventions (Sampogna et al., 2021). Beyond the rare public call for macro-level income protection during an economic crisis, the idea of mitigating mental disorders, and specifically major depressive disorder, through the spending generosity of social welfare programs, is rarely discussed (McDaid, 2021; Ribanszki et al., 2022; O'Campo et al., 2015). Any calls for major depressive disorder mitigation in European populations through social welfare spending are also drowned out by other academic perspectives that stress the importance of non-spending focused labor policy improvements or other non-spending related policy changes aimed at bolstering the mental health of the working population (Peters et al., 2022, p. 192; World Health Organization & International Labour Organization, 2022). Clearly, the rise of major depressive disorder across many country contexts is a complex issue with many competing causal understandings, and just as many competing possible solutions (Collins, 2020). There is little debate, however, that public policymakers have a role to play in addressing the mental health levels of their country populations, and have a need for better information on the specific tools they may be able to use to address the issues of major depressive disorder and depressive symptoms in their population (Collins, 2020). Ideally, this work can provide value to policymakers by providing new and novel solutions to addressing individuals' depressive symptoms and mental distress. Through non-biomedical and psychosocial intervention approaches, this thesis research hopes to broaden knowledge on economic interventions to individual-level depressive symptoms in EU countries.

1.2 Purpose and Research Question

This study takes its theoretical foundation from scholars' claims that there are impactful social and economic determinants of individual mental health (Marmot & Wilkinson, 2005; Silva et al., 2016; Rose et al., 2020). We focus specifically on the proposition that there are significant *economic determinants* to mental health, and thus that there are also economic determinants to major depressive disorder, and to depressive symptoms (Silva et al., 2016; Rose et al., 2020; Garcy & Vågerö, 2013; Davies et al., 2015). Therefore, it follows that there should also be *economic solutions* and ways to mitigate individual mental distress in European populations (Naik et al., 2017; O'Campo et al., 2015; Thomson et al., 2016; Bergqvist et al., 2013).

The aim of this thesis is to investigate the research pathways that remain unstudied or understudied regarding the impact of national social expenditure levels on individual depressive symptoms, which are the main indicators of major depressive disorder. In order to do this, this paper engages time-series social program expenditure data and three waves of cross-sectional European Social Survey survey (ESS) data across 16 European countries with fixed effects regression models to explore statistical interactions between country-level social protection spending categories and the depressive symptoms of individuals within those countries who may be psychologically benefited by such spending. We have also identified an entire field of social spending, national old-age + incapacity-related social program expenditure, that has never been researched independently in relation to the depressive symptoms of individuals. Our research focus is on depressive symptom levels in individuals across EU country contexts because major depressive disorder is the most common and widespread form of mental distress (Collins, 2020).

This study will investigate the following research question:

RQ: What effects does the expenditure level of European government social policy programs have on an individual's depressive symptom outcomes within those countries?

H1: *Increases in European government social expenditure on all* ***family policy related programs*** *have an* ***inverse*** *relationship with the population of parents' depressive symptoms. Furthermore, we believe that increases in government spending on family policy related programs will have a small but significant inverse relationship with depressive symptoms in a larger sample population of individuals.*

H2: *Increases in European government social expenditure on* ***old-age + incapacity-related programs*** *have an* ***inverse*** *relationship with the level of depressive symptoms in the older population (individuals 65+). We also believe that increases in spending on old-age + incapacity-related programs will have a smaller but still significant inverse relationship with depressive symptoms across a larger sample of individuals who are not over age 65.*

H3: *Increases in European government* ***total social expenditure*** *have an* ***inverse*** *relationship with the whole country's population's depressive symptoms. We expect this inverse relationship between total social expenditure and depressive symptoms to hold across specific populations such as parents and those over age 65+.*

These hypotheses are formed based on our theoretical foundation of the economic determinants of depressive symptoms. Our understanding of the theory follows that because there are impactful economic determinants to individual-level mental health outcomes, spending on social programs that directly alleviate economic hardship and supports individuals economically should have a significant effect on those individuals' levels of depressive symptoms. Thus, we believe that the greater the economic support the government provides through social expenditure, the lower individuals' depressive symptom levels should be. We use this theory to hypothesize that specific population groups, women and the elderly (individuals aged 65+ in the population) will be most affected by each social expenditure category, family policy, and old-age + incapacity-related programs specifically. We further hypothesize that the social expenditure levels in these categories, family policy programs, and old-age + incapacity-related programs, will have an inverse relationship to the level of depressive symptoms in the entire population.

2. Theory and Prior Research

This section commences by explaining overarching definitions and concepts we engage with throughout the study. It then proceeds with the meta-theoretical claims adopted in our attempt to answer the research question. It is followed by a theoretical overview of social and economic determinant theories of health and mental health. We then explain our own theoretical approach, the social expenditure approach. Finally, to finish the theory and prior research section we explore research on theorized interventions to health inequalities that led us to our hypotheses, and we present our theoretical framework.

2.1 Ontological and Epistemological Claims

Before we examine the theory underpinning this thesis and explain our research design, it is relevant to establish the ontological and epistemological positioning of this research. Ontological assumptions are best explained as the assumptions about the existence of reality and society, and epistemological assumptions are explained as ideas about what and how knowledge can be known (Zachariadis et al., 2013 p. 856) Acknowledgement of this positioning is critical, as different ontological and epistemological positions and approaches tend to dictate the chosen scientific method(s) of inquiry into a research topic (Bryman, 2016). This thesis's ontological position is a 'critical' realist (CR) approach (Bhaskar, 1989 as cited in Zachariadis et al., 2013). Critical realism ontologically is rooted in realist philosophy, such that it holds that there is the existence of a foundational reality that exists separately from our knowledge of it (Zachariadis et al., 2013 p. 856). However, epistemologically, critical realism as an approach emphasizes the human generation of knowledge, ie. the socially produced knowledge of this reality, and recognizes that this independent reality may not be fully observable or measured perfectly currently with the tools we have. Thus causal statements about the social world have a degree of relativity to them, and complex causal reasonings may reign, with multiple valid theories existing at once that can explain the foundational reality of the world, some better than others (Zachariadis et al., 2013). This study takes the position that there are generalizable truths of social phenomena that can be gleaned through the observation of our social reality and that these truths can hold across contexts. However, we also contend that our causal statements are not universal truths and cannot be automatically translated to other similar processes, because social phenomena, such as an individual's depressive symptoms, are influenced by structures that cannot always be directly observed.

Applied to our study and mental health research, a CR position perfectly entails our research's focus on biological/psychological realities that have social determinants and social meanings, which then co-constitute the reality we are attempting to explore (a mixing of positivist and interpretivist positions) (Pilgrim, 2014). Critical realism guides our questioning of mental health outcomes by positioning us to ask research questions that do not subscribe to a priori casual contentions Pilgrim (2014) contends that mental health research from a critical realist perspective "tends away from diagnosis to one of open and context-specific curiosity: Which antecedent aspects of their life might have made them prone to present to others in this distressed or unintelligible way?" (p. 14). As Pilgrim (2014) further notes, a CR approach to mental health research looks further than the biological, and focus on singular casualties, instead focusing on complex and contextual casualties for socially understood conditions that may have biological and psychological realities. This is to say that a CR approach to mental health research predicts open systems that may contain semi-regular trends, and particularly "expects that a single outcome might arise from a range of antecedent generative mechanisms in various context-bound permutations" such as in depressive symptoms related to social conditions (Pilgrim, 2014, p. 14). This is why our study situates itself with exploratory research to find out if a variety of government social spending policies correlate with changes in subjective depressive symptoms, and how these multiple social and economic stimuli may have causal relationships with biological realities over multiple country contexts, or not.

Critical realist approaches can methodologically engage in qualitative and quantitative research (Bryman, 2016; Zachariadis et al., 2013). In this study, a quantitative methodological approach can be used to understand potential causal effects that government social expenditure spending may have on individuals' subjective psychological feelings (depressive symptoms).

2.2 Definitions & Concepts

Now we provide definitions and conceptual overviews of the language that will be used in this research.

First, we use the term 'social policy program expenditure' to denote state-level aggregate spending on specific welfare program categories. One can think of this as a measurement of welfare generosity in terms of social spending for specific welfare program groups. This study also uses some interchangeable terms, such as social expenditure, social welfare expenditure, and social protection expenditure. All three of these terms in this study refer to the same thing:

welfare generosity via social spending. This variance in terminology is present across the current literature on social expenditure approaches to understanding public health outcomes (Dahl & Van der Wel, 2013; Álvarez-Gálvez & Jaime-Castillo, 2018; Sieber et al., 2022). For the purposes of our study, we differentiate and specify the type of social expenditures we operationalize by using specific language that the Organisation for Economic Co-operation and Development (OECD) Social Expenditure database uses to categorize government spending pools, such as family policy program spending, and old-age + incapacity-related program spending (OECD, 2023).

This study draws the definition of major depressive disorder from the Diagnostic and Statistical Manual of Mental Disorders, 4th Edition (DSM IV), which is a manual published by the American Psychiatric Association that includes almost all currently recognized mental health disorders (American Psychiatric Association, 1994). Accordingly, major depressive disorder can be characterized in an individual by the *frequent* presence of the majority of symptoms including depressed mood, diminished pleasure in daily activities, significant weight loss or weight gain or decrease in appetite, insomnia or hypersomnia, psychomotor agitation or retardation, fatigue or loss of energy, feelings of worthlessness, suicidal ideation, diminished ability to think (American Psychiatric Association, 1994). Following this definition of major depressive disorder as simply the frequent presence of depressive symptoms, the critical conceptual definition we employ in our research is our categorization of depressive symptoms. In this study, we measure an individual's level of depressive symptoms through a widely used depressive symptoms measurement tool, the Center for Epidemiologic Studies Depression Scale (CES-D 8), a shortened version of the original 20-question CES-D survey measurement tool that has been used across the literature to measure an individual's level of depressive symptoms (Radloff, 1977; Van et al., 2010; Niedzwiedz et al., 2016). The CES-D is widely used to measure "the frequency and severity of symptoms related to a DSM IV criterion for major depressive disorder" and thus we use it to define an individual's level of 'depression' and thus risk for major depressive disorder in our study (Van et al., 2010, p. 397). This study further employs the CES-D 8 tool to measure the concept of depressive symptoms because it is used by the European Social Survey (ESS), our survey sample, across every round of survey data collection used in this study.

2.2 Determinant Theories of Health & Mental Health

2.2.1 Social Determinants of Health

There is an ongoing debate about the primacy different causal mechanisms may have in explaining health outcomes amongst populations. Public health researchers such as Marmot and Bell, have determined that health inequalities in a population such as reduced life expectancy and increased burdens of disease are influenced by individuals' social position and status (Marmot & Bell, 2016). This idea is conceptualized as the "social gradient" of health, in which the lower an individual is in social status, the higher an individual's risk is for negative health outcomes and lower life expectancy (Marmot & Bell, 2016). Differences in social status are theorized to affect health outcomes because of the material inequalities they represent, ie. the unequal distribution of material resources amongst individuals in the population (Marmot & Wilkinson, 2005; Marmot et al., 2008). Researchers investigating the social gradient of health in populations, focus on what they term ‘social determinants of health, which is how the ways in which populations live and are situated socially impact their health outcomes (Marmot & Wilkinson, 2005; Marmot et al., 2008, Marmot & Bell, 2016).

Within this framework of the social determinants of health, there is a distinction made between ‘upstream’ and ‘downstream’ social influences and determinants (Graham, 2009; Braveman et al., 2011). ‘Upstream’ social determinants refer to broader social structures and an individual's place in them (e.g. economic opportunity for an individual) while ‘downstream’ social determinants are the behaviors and living conditions that can be a result of the ‘upstream’ conditions (e.g. biological risk factors, behaviors with associated health risks) (Graham, 2009). This study focuses on ‘upstream’ social determinants of health, following ideas from researchers such as Braveman and colleagues who contend that ‘upstream’ social determinants are the primary causes of ‘downstream’ social determinants (Braveman et al., 2011). Other scholars in the field of health inequalities such as Douglas similarly contend that the primary research focus to alleviate health inequalities must be a focus on ‘upstream’ social determinants, especially the current economic paradigm into which individuals are locked (Douglas, 2016; Macintyre et al., 2018, p. 2).

The ‘upstream’ social determinants of health, however, are vast. Looking at the table below, we can see just how many individual and interconnected factors may be at play in impacting an individual's health outcomes (Artiga & Hinton, 2018 as cited by Christina Nuñez Ross, 2018). This study focuses broadly on ‘upstream’ social determinants of health, and more specifically we focus on the economic categories within the ‘upstream’ social determinants of health. Using the table below as a reference, the ‘economic’ focused categories are *Economic Stability* and some of the items in *Necessities*, as well as items in *Development & Education* such as ‘Early Childhood Development’ and ‘Quality and Availability of Education’.

Table 1 - The 'Upstream' Social Determinants of Health

Economic Stability	***Necessities***	***Demographics & Social Context***	***Environment***	***Development & Education***
Employment Status *Income Level* *Health Insurance Status* *Expenses* *Financial Safety Net*	*Access to Housing* *Access to Food* *Access to Clean Drinking Water* *Air Quality* *Utilities*	*Gender Inequality* *Sexual Orientation/Discrimination* *Ethnicity/Racism* *Cultural Identity* *Language Barriers* *Immigration Status* *Social Network & Capital*	*Crime Rate* *Access to Transportation* *Safety of Built Environment* *Parks/Green Space* *Recreational Opportunities* *Availability of Healthcare*	*Early Childhood Development* *Adverse Childhood Experiences* *Quality and Availability of Education* *Health Literacy*

(Christina Nuñez Ross, 2018)

This study chooses to investigate mainly economic-focused determinants because health scholars such as Friedli contend that to focus on the social, psychosocial, or community-based explanations for unequal health outcomes is to effectively cover the "fundamental causes of distress", which are the economic factors (Friedli, 2016, p. 216). In one of the most comprehensive studies into the relationship between low-income and poor health outcomes, Lynch and colleagues used income measurements from three different time periods to explore the "cumulative effect of economic hardship" on health, concluding that "sustained economic hardship leads to poorer physical, psychological, and cognitive functioning" (Lynch et al., 1997, p. 1889).

2.2.2 Economic Determinants of Mental Health

Research in the field of social and economic determinants of health has come to investigate all types of health outcomes that social determinants may touch, including individual mental health outcomes, such as rates of major depressive disorder (Silva et al., 2016; Macintyre et al, 2018; Alegría et al., 2018). Macintyre and colleagues stress the importance of social and economic determinants to health in relation to mental health, stating that an analysis of economic determinants "may be particularly relevant for mental health, where psychological conceptualizations may predominate" (Macintyre et al., 2018, p. 3).

Silva et al. conducted the largest narrative review of published evidence on the association between mental health and sociodemographic and economic factors (Silva et al., 2016). In their review, the authors examined 150 papers on the relationship between mental health and socioeconomic factors, finding 78 studies that reported associations between individual-level factors and mental health (Silva et al., 2016, p. 283). The authors reported in the review that the main factors shown to have a statistically significant independent association with worse mental health included many economic determinants such as low income, low level of education, low socioeconomic status, unemployment, financial strain, and deteriorated housing (Silva et al, 2016, p. 283).

A plethora of research investigating income and individual mental health outcomes from Western country contexts has existed since at least the 1990s (Weich & Lewis, 1998; Zimmerman & Katon, 2005; Wildman, 2003). Weich and Lewis's (1998) prospective cohort study in the U.K. showed mild associations between income and mental health outcomes. Income levels have continued to be shown to be a strong determinant of mental health across populations spanning the U.K., U.S., EU, and many other country contexts (Zimmerman & Katon, 2005; Silva et al., 2016, Lorant et al., 2007; Laaksonen et al., 2007). More recent research into the economic determinants of mental health also concludes that low economic support, and income inequality specifically, are major determinants of individual mental health outcomes (Lorant et al., 2007; Amroussia et al., 2017).

Other frequently researched economic determinants of mental health outcomes are events such as experiences of unemployment and country-level rises in unemployment rates due to recessions and economic shocks (Norström & Grönqvist, 2015; Stuckler et al., 2009; Nordenmark et al., 2006; Fountoulakis et al., 2015; Brydsten et al., 2018; Reibling et al., 2017). Reibling and colleagues, looking at European country populations through the European Social Survey (ESS), found that following the 2007/8 financial crisis depressive symptoms of individuals across European countries increased when individuals had no or precarious employment (Reibling et al., 2017). Brydsten et al. relay similar findings regarding mental health outcomes and employment in the context of northern Sweden using an entirely different survey population and mental health outcome measurement (the GHQ-12) (Brydsten et al., 2018). These findings across populations and using a variety of methodological tools suggest a strong correlation between mental health outcomes and employment status across European country contexts.

Thus far we have discussed the most often researched economic determinants of mental health: income level and employment status ie. work and income. We have also introduced research that finds a correlation between relative deprivation (inequality) and mental health outcomes. We introduce this theory to show that the economic determinants of mental health are real, and strongly correlated across time, political context, and country context. In our next section we explain our theoretical approach, the social expenditure approach, which is the theoretical approach we chose to be able to investigate potential mental health interventions in greater depth and specificity.

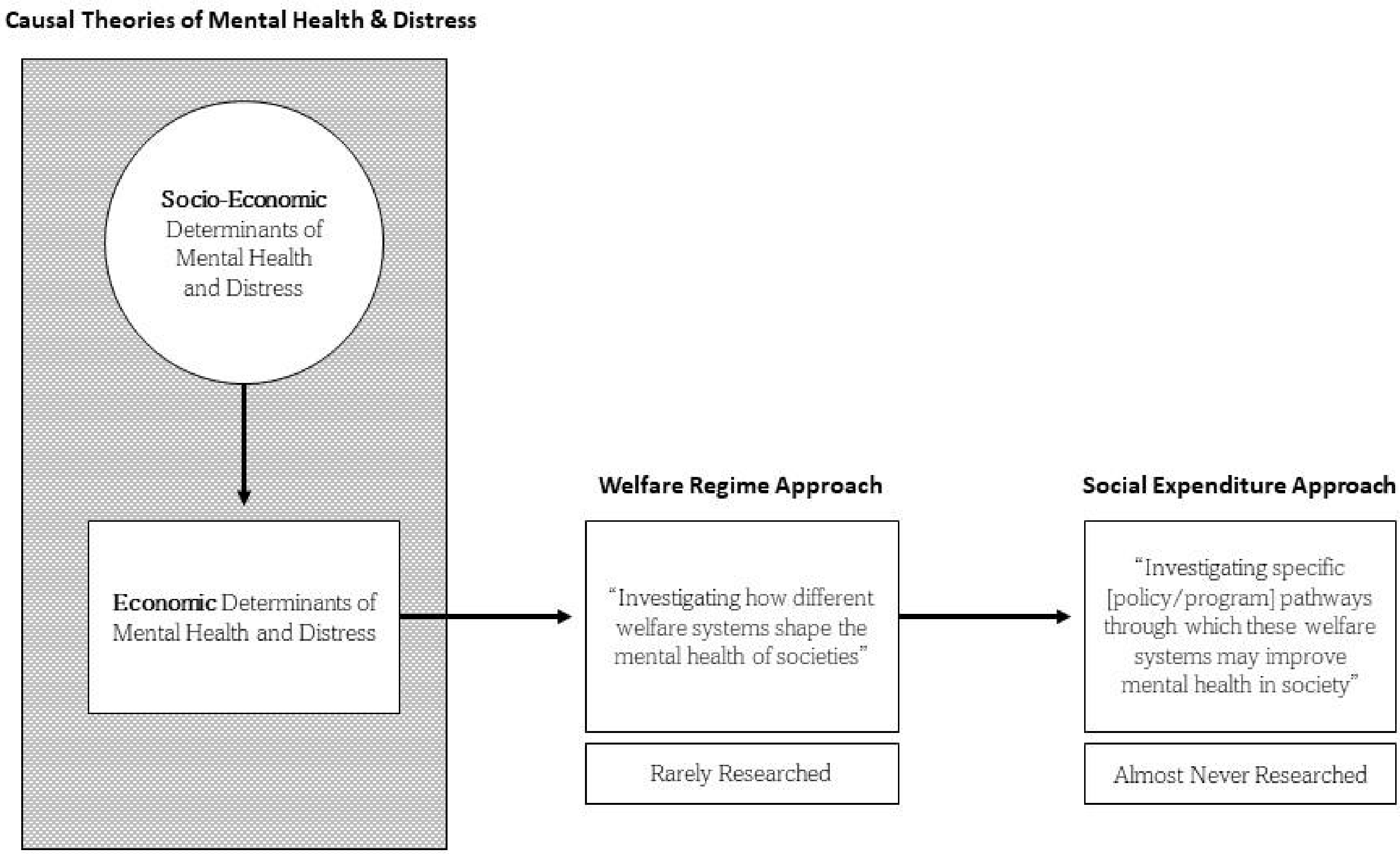
2.3 Investigating the Economic Determinants of Mental Health

There are multiple ways that researchers who subscribe to determinant theories of health and mental health have attempted to approach researching the determinants themselves (Naik et al., 2017; Khan et al., 2016; Ribanszki et al., 2022). As we presented in the previous section, lots of research has been done in past decades on country-level longitudinal population studies, and cross-sectional longitudinal studies looking at overall associations between a medley of determinant factors and a specific mental health outcome (Lorant et al., 2007; Garcy & Vågerö, 2013; Reibling et al., 2017). The umbrella and systematic reviews that look at all these studies find overwhelming evidence for correlations between economic realities, and mental health outcomes (Macintyre et al., 2018; Naik et al., 2017; Silva et al., 2016).

Following this evidence of a relationship between economic determinants and mental health outcomes, questions then arise about mechanisms that may influence mental health outcomes by changing those economic determinants. In this section, we discuss two different approaches to researching how the welfare state and its programs can change underlying 'upstream' economic determinants of mental health. The two theoretical approaches that attempt to answer how government economic interventions impact mental health outcomes we discuss are the welfare regime approach and the social expenditure approach.

In the figure below, our elaboration of Ribanszki and colleagues' categorization of two theoretical approaches, one can see that both approaches draw from the theory of economic determinants of mental health.

Figure 1 - Two Frameworks Investigating Impacts of Economic Interventions on Individual Depressive Symptoms



Text from (Ribanszki et al., 2022)
Own Elaboration

Both approaches seek to answer similar questions surrounding how mental health outcomes are shaped by economic determinants. As Thomson and colleagues note, the modern European welfare state itself is a determinant of health and mental health, in that it touches, changes, or provides many other 'upstream' economic and health determinants (Thomson et al., 2016). This is due to the fact that all European welfare states contain policies and programs that define most of the country's health policy and social policies (including economic support policies) (Thomson et al., 2016). It is apt to think of the welfare regime approach as the macro-level, and the social expenditure approach as a deeper examination of the macro-level by looking at particular things within the macro-level economic construct (in this case the welfare state). As one can see in the figure above, we can understand the social expenditure approach as a continuation, or deepening, of welfare regime approaches. What is meant by this is best summarized by Ribanszki and colleagues, who write that welfare regime approaches aim to understand how welfare systems impact mental health outcomes, and social expenditure approaches concern themselves with how specific mechanisms (policy/programs) within the welfare systems impact mental health outcomes (Ribanszki et al., 2022). This relationship between the approaches is illustrated above through the use of arrows, showing the flow from the welfare regime approach to the social expenditure approach. As we will discuss next, the welfare regime approach is the most widely used in this scholarly community but is still under-researched (Ribanszki et al., 2022). The social expenditure approach historically has been unpopular and is only contemporarily becoming more researched, with still very few scholars using this approach (Ribanszki et al., 2022).

2.3.1 The Social Expenditure Approach

Instead of a welfare regime approach, this study adopts a social expenditure framework approach. Put simply, a social expenditure approach means analyzing the specific impact of social spending on an outcome, in this case, depressive symptoms comparatively. Measuring cross-national differences and policy impacts based on state-level social protection expenditure and not primarily on welfare typologies has been frequently suggested as a research route (Castles, 2002; Castles, 2009; Hessami, 2010). However, research into individual *health* outcomes from a social expenditure approach is sparse (Sieber et al., 2022; Dahl & van der Wel, 2013; Álvarez-Gálvez & Jaime-Castillo, 2018). Research looking at the association between state social protection expenditure and mental health outcomes can be attributed to only one other paper (Niedzwiedz et al., 2016).

One might question how a social expenditure approach is that different from a welfare regime approach, when measuring social protection spending and using the spending data as a measure of analysis with health outcomes sounds like it would closely replicate results that you would get from looking at associations between welfare regime and health outcome. A social expenditure approach lets us attempt to view the association between specific policies, or groups of policies (such as in this study 'family policy related programs') and health outcomes, instead of being limited to categorization and analysis based on a larger typology. Critics of the social expenditure approach to analysis have claimed that only looking at social protection spending totals leaves out critical non-spending factors such as labor market regulation, or other non-spending related social protections (Ribanszki et al., 2022). We do not disagree that non-spending social protection policies likely have large explanatory power in regard to health outcomes. In fact, lots of regulatory and labor market changes unrelated to spending have been previously researched, and found to have effects on health and mental health outcomes such as depression and suicide (McDaid, 2021). We find the argument that one must use welfare regime typologies to analyze welfare policies' effects on mental health outcomes because using spending data would exclude certain factors to entirely miss the point of social protection expenditure research. The point is to attempt to isolate and control for non-spending related factors and instead look solely at the channels of social protection expenditure and see if there are causal associations between just spending, and mental health outcomes such as depressive symptoms.

Other critiques of this approach have been historically that looking at aggregate social protection spending data would exclude from an analysis how expenditure is allocated amongst the population and thus could hide effects (ie. all the money goes to the employed, or those who occupy specific social positions) (Esping-Andersen, 1990, as cited in Ribanszki et al., 2022). This study agrees with Castle's (2002) argument that contemporary welfare state data has gotten much more expansive and comprehensive, and thus it is easy to now see the flow of spending from start to end. We contend that with large-scale databases such as the OECD's Social Expenditure Database (SOCX), it is now possible to avoid the pitfall of simply analyzing a large 'black box' expenditure that Esping-Andersen and others have pointed out, and instead, we can use this data to evaluate the impact on depression of social spending of many different types in far greater detail than welfare regime categorization.

We find previous critiques on a social expenditure approach to be outdated due to changes in the availability of high-quality social protection spending data, and the social expenditure framework to be underutilized in exploring the relationship between social protection spending and depression and depressive symptoms. This theoretical framework forms the foundation of this thesis's research question: What mitigating effects does the spending level of certain focused European government social expenditure programs have on individual-level depressive symptom outcomes?

2.4 Theoretical Framework: Exploring Hypotheses

As we have discussed previously in this chapter, many socioeconomic conditions directly affect a population's mental health outcomes. In this study, we use the social expenditure framework, to theorize that specific welfare and social protection program spending acts as a *mitigating* factor to individual depressive symptom outcomes.

In this sense, this study uses the social expenditure framework approach to hypothesize that *larger* amounts of state social protection program spending will *decrease* individuals reported depressive symptoms across many European country contexts. An expectation for an *inverse* relationship between social protection program spending and individual depressive symptoms (which is measured through CES D-8 score) is stated across all of our three hypotheses. This part of our hypothesis comes from scoping reviews and other meta-analyses of research done regarding the effect of welfare state programs on health, such as that of Khan et al. (2016), and Naik et al. (2017). Both of these reviews of research on the economic determinants of health stress that interventions (ie. social protection programs) moderate or mitigate negative health outcomes when present, and we hypothesize that this relationship would also hold for mental health outcomes such as depressive symptoms across similar European country contexts. While we hypothesize an inverse relationship between social protection spending and depressive symptoms in all 3 of our hypotheses, H3 represents this claim in its simplest form, as it hypothesizes the inverse relationship between individual depressive symptoms and total government social policy program expenditure:

H3: *Increases in European government* ***total social expenditure*** *have an* ***inverse*** *relationship with the whole country's population's depressive symptoms. We expect this inverse relationship between total social expenditure and depressive symptoms to hold across specific populations such as parents and those over age 65+.*

For our other hypotheses, H1 and H2, we chose specific types of social protection spending categories as the majority focus for this study for a few reasons due to the current state of the literature on this topic.

First, the association between depressive symptoms and social protection expenditure on family policy programs has only been studied once (Niedzwiedz et al., 2016). We recognize Niedzwiedz and colleagues' findings that family policy programs do have an inverse relationship with social protection expenditure across many European government contexts. However, this thesis study adds an additional round of data from the ESS 7 in 2014 and does not mirror the countries analyzed in Niedzwiedz et al. 's 2016 research, although countries between this study and theirs overlap (ESS ERIC ESS 7, 2018). We also use a different method concerned with finding within-country effects of expenditure change, and through our method control for country GDP.

H1: *Increases in European government social expenditure on all* ***family policy related programs*** *have an* ***inverse*** *relationship with the population of parents' depressive symptoms. Furthermore, we believe that increases in government spending on family policy related programs will have a small but significant inverse relationship with depressive symptoms in a larger sample population of individuals.*

We also arrived at our H1 hypothesis surrounding family policy related program spending due to previous research done by Avendano et al. (2015) and Mandal (2018), two studies that investigated the relationship between depression and paid maternity leave schemes across European countries and in the U.S. respectively. Avendano and colleagues (2015) studied if different levels of paid maternity leave generosity impacted women's depressive symptoms in later stages of life, finding that women who did have access to paid maternity leave during the birth of a first child had lower depressive symptom scores later in life (p. 45). Mandal (2018) found that in the U.S. amongst women who had just given birth, depressive symptoms that increased by a return to work were reduced when women received paid maternity leave (p. 1470). In both cases, we see that the availability of paid maternity leave mitigates women's depressive symptoms. Paid maternity leave is in many European countries a government program counted by the OECD SOCX database in the family policy program category, and expansions of paid leave, such as for fathers, are also counted by spending amounts. Thus we expect countries with these programs to similarly have a mitigating effect on all parents' depressive symptoms.

We chose our second hypothesis, H2, due to a lack of literature on social protection spending effects on mental health for older individuals.

H2: *Increases in European government social expenditure on **old-age + incapacity-related programs** have an **inverse** relationship with the level of depressive symptoms in the older population (individuals 65+). We also believe that increases in spending on old-age + incapacity-related programs will have a smaller but still significant inverse relationship with depressive symptoms across a larger sample of individuals who are not over age 65.*

Costa-Font (2008) writes that socioeconomic determinants of health (and mental health) amongst older populations in European country contexts are more complex, as older individuals may rely more on social protection programs, build lifetime equity (ie. housing), and government incapacity-related benefits (p. 478). Because of the economic reliance of those who cannot work anymore or could never work on non-market forces such as pensions/benefits, we hypothesize that increases in program generosity of old-age + incapacity-related programs will mitigate depressive symptoms amongst older populations.

3. Data and Method

3.1 Data

In order to perform our analysis, our study is using three waves of panel data from the European Social Survey (ESS), as well as three years of country-level cross-national social expenditure data, which is taken from the Organisation for Economic Co-operation and Development (OECD) social expenditure (SOCX) database. We are also using 3 different samples, all created from the larger total ESS round survey samples for our different waves of analysis. We call these different sample configurations S1: Parents Sample (**N = 30064)**, S2: Age 65+ Sample (**N = 21309)**, and S3: Total Sample (**N = 91859)**. These survey samples are made from the three ESS rounds we use in our analysis. Explanations of how we structure the samples are given below.

The panel data from the ESS consists of data taken from the third 2006/07, sixth 2012/13, and seventh 2014/15 waves of the survey. The ESS is a cross-sectional survey conducted every 2 years and is representative of individuals aged 15 years and over who reside in the sampled household in each country, regardless of nationality, citizenship, or language (European Social Survey Fieldwork Summary and Deviations, 2023). Individuals were selected by strict random probability methods at every stage (European Social Survey Sampling, 2023). ESS response rates vary by country, but with total sample sizes in each ESS wave close to 50,000, the ESS can be considered a robust and statistically significant random sample (European Social Survey Sampling, 2023). Response rates amongst the countries observed vary significantly, from 46.0 % in France to 72.8% in Portugal in the 2005/6 ESS Round 3, to 33.8 % in Germany to 77.1 % in Portugal in 2012/13 ESS 6 Round, to 31.4% in Germany to 67.9% in Spain in 2014/15 ESS 7 Round (ESS ERIC ESS 3 Data Documentation, 2018; ESS ERIC ESS 6 Data Documentation, 2018; ESS ERIC ESS 7 Data Documentation, 2018). Importantly, all three rounds of our ESS data in each country of analysis (our list of 16 countries is listed below) have been shown, as a whole, to be statistically relevant across the country's population (European Social Survey Sampling, 2023).

All country-level disaggregated and aggregated public social program expenditure data is taken from the OECD SOCX database for the exact years of ESS data collection (2006, 2012, and 2014) (OECD, 2023). We have chosen to take net public expenditure on social protection from the year during the ESS round following research done by Niedzwiedz et al., (2016) because there is unavailable full net public expenditure on social protection categories for our countries of interest in some of the initial years of ESS sampling. Following other research from Parbst & Wheaton (2023), we have used SOCX data from 2014 for ESS round 7, even as this round was conducted up until the 13th of December, 2015, and because data collection of the ESS survey data was mostly done during the 2014 year, and the ESS themselves state it is primarily relevant as 2014 survey data (European Social Survey Sampling, 2023; OECD, 2023).

For both the data used from the ESS waves and the data used from the OECD's SOCX database, we are including the following 16 countries in our analysis: Belgium, Denmark, Switzerland, Germany, Estonia, Spain, Finland, France, United Kingdom, Ireland, Netherlands, Norway, Poland, Portugal, Sweden, and Slovenia.

Countries excluded from this analysis were Austria, Bulgaria, Czech Republic, Cyprus, Hungary, Iceland, Israel, Lithuania, Slovakia, Ukraine, and the Russian Federation. These exclusions were either due to the unavailability of the relevant social expenditure data or inclusion in the ongoing ESS at only one or two points in time. Because this research is concerned with the association between social spending and depressive symptoms *within* countries over time, we find it valuable to only include country data in our study that can be found across all three of the time periods, even if this means a lower overall country sample size for our study.

We take individual data from the 2006, 2012, and 2014 ESS rounds, and we pool the data (putting multiple ESS rounds of data together) by sample. We have sorted the survey panel data in three different ways using a listwise deletion technique, a common way to trim sample data into the form needed for analysis (Parbst & Wheaton, 2023). We have first cleaned our data through the exclusion of individuals who do not provide age and parental history demographic answers, or answers on the CES-D 8 questions. Afterward, we limited our total sample into focused smaller samples for analysis, in a process described below.

For our first sample (S1: Parents Sample), used in our analysis concerning family policy program expenditure and depressive symptoms, we have limited all three rounds of the ESS data to only include individuals who identify as a parent in the survey (this is identified through one demographic question answered by survey participants). The identifying question is:

"Have you ever had any children of your own, step-children, adopted children, foster children or a partner's children living in your household?"
(ESS ERIC ESS 3, 2018, ESS ERIC ESS 6, 2018; ESS ERIC ESS 7; 2018)

Survey respondents may answer either Yes/No, or with a variety of other values that are for the purpose of this research all counted as missing values and excluded from the sample. Those who answer Yes, a value of (1) in the survey, are included in this sample.

For our second sample (S2: Age 65+ Sample) which we use for our second analysis, concerning old-age + incapacity-related program expenditure and depressive symptoms, we have limited the ESS data to only include individuals who are aged 65 or older (this is also identified through a demographic question answered by survey participants). The identifying question is:

"And in what year were you born?"
(ESS ERIC ESS 3, 2018, ESS ERIC ESS 6, 2018; ESS ERIC ESS 7; 2018)

In order to determine who is equal to or over the age of the 65 at time of survey response, we luckily can simply look at the calculation done inside of the ESS itself, "Age of respondent, calculated" which gives us the respondent's calculated age.

For our third and final sample (S3: Total Sample), used in our overall social protection expenditure and depressive symptoms association within-country analysis, we have included the full sample of individuals in all 3 ESS rounds of choice, without the previous limitations based on demographic factors.

We can see a visual breakdown of sample sizes in our three samples in the table below by country and in total for each sample.

Table 2 - Disaggregated Country Sample Sizes Sorted by Parental Status, Age, and in Total for ESS Rounds 3, 6, and 7.

	ESS Round 3			ESS Round 6			ESS Round 7		
Country	**Parent**	**Age 65+**	**Total**	**Parent**	**Age 65+**	**Total**	**Parent**	**Age 65+**	**Total**
Belgium	455	352	1797	527	385	1867	499	357	1769
Denmark	590	305	1482	602	385	1642	568	341	1499
Switzerland	616	412	1802	389	308	1492	391	328	1531
Germany	963	652	2901	1025	675	2955	1063	738	3041
Estonia	464	362	1497	922	599	2365	810	534	2037
Spain	355	374	1874	386	371	1885	407	415	1925
Finland	799	425	1891	835	539	2193	789	579	2080
France	704	392	1986	876	534	1968	761	474	1915
United Kingdom	829	594	2394	914	678	2282	918	672	2250
Ireland	325	448	1784	657	533	2620	630	563	2376
Netherlands	567	390	1885	677	480	1844	668	495	1917
Norway	563	273	1747	536	277	1617	484	291	1433
Poland	274	271	1705	430	340	1887	362	327	1600
Portugal	1059	642	2218	854	645	2149	472	422	1264
Sweden	690	359	1919	673	440	1846	686	489	1787
Slovenia	278	294	1469	376	264	1256	346	286	1216
Totals (N=)	**9531**	**6545**	**30351**	**10679**	**7453**	**31868**	**9854**	**7311**	**29640**
Sample #1: Parent	**N = 30064**								
Sample #2: Age 65+	**N = 21309**								
Sample #3: Total	**N = 91859**								

As we can see in the table above, our chosen ESS Rounds vary in total sample size from 31868 to 29640. Our original sample sizes before listwise deletion due to missing or null answers on the CESD8 questions entailed a sample size loss across all three of our samples. In Sample #1, our sample loss was 413 survey participants. In Sample #2, our loss was 125 survey participants after listwise deletion. In Sample #3, our sample loss was 290 survey participants after listwise deletion. For our total sample #3, we can see that our pooled total sample is 91859, and the within-country variance of the sample per-round disaggregated is anywhere from 1216

(Slovenia, ESS Round 7) to 3041 (Germany, ESS Round 7). Within-country sample size variance of our Sample #1 and Sample #2 disaggregated samples per year is anywhere from 273 (Norway, ESS Round 3) to 738 (Germany, ESS Round 7) for our Age 65+ Sample #2, and 277 (Slovenia, ESS Round 3) to 1063 (Germany, ESS Round 7) for our Parent Sample #1. We lose a large portion of the total sample when we limit by age, from 91859 to 21309, and a similarly large limitation is imposed on our total sample when we limit to those who have had a child at any time in their life, from 91859 to 30064. Our post-list deletion pooled sample sizes for our three analyses are: **N = 30064 for Parent Sample #1, N = 21309 for Age 65+ Sample #2, and N = 91859 for Total Sample #3.**

3.1.1 Dependent Variable

The CES-D 8 survey questions in our chosen three waves of ESS panel data add up to an indexed score which we use as our dependent variable. Eight questions specifically are of particular use for our study. These questions are taken from the aforementioned and widely used Center for Epidemiologic Studies Depression Scale 8 (American Psychiatric Association, 1994). As we have previously discussed, the CES-D 8 is a widely used measure of depressive symptoms across different country contexts, and has been validated for use in European demographic contexts specifically (Van de Velde et al., 2009). Respondents are asked to indicate how often in the past week previous to the survey they felt or behaved in a certain way ranging from 'none or almost none of the time' to 'all or almost or all of the time'. The CES-D 8 response values in the standard CES-D 8 form are 4-point Likert scales, with a range of 0 to 3, however, the ESS measures them with a range of 1-4 (ESS ERIC ESS 3, 2018; Van de Velde et al., 2009). See the table below for a full layout of questions, and the scoring category as it is presented in each ESS round.

Table 3 - Dependent Variable, Depressive Symptoms

Variable	Literal Question	Category
Depressive Symptoms **Combination of 8 Variables:** **1. Effort** **2. Joy** **3. Sadness** **4. Loneliness** **5. Motivation** **6. Depression**	*I will now read out a list of the ways you might have felt or behaved during the past week. Using this card, please tell me how much of the time during the past week…* 1. *...you felt that everything you did was an effort?* 2. *...you enjoyed life?* 3. *...you felt sad?* 4. *...you felt lonely?* 5. *...you could not get going?*	(1) None or almost none of the time (2) Some of the time (3) Most of the time (4) All or almost all of the time *(All other codes = missing variables removed from analysis)*

7. **Happiness** 8. **Sleep**	*6. ...you felt depressed?* *7. ...you were happy?* *8. ...your sleep was restless?*	

European Social Survey (ESS ERIC ESS7, 2018, ESS ERIC ESS6, 2018, ESS ERIC ESS3, 2018)
Own Elaboration

As seen in the table above, the eight questions we take from the ESS panel data together are about how many times in the last week the individual… felt depressed, felt everything you did was an effort, your sleep was restless, you were happy, you felt lonely, you enjoyed life, you felt sad, and you could not get going (ESS ERIC ESS 3, 2018; American Psychiatric Association, 1994). Our dependent variable is created from our ESS panel data by adding the individual results of all 8 questions in the data and then creating a variable from it called CES-D 8 score. We justify the reliability and validity of our dependent variable (a 'depression score' measure through depressive symptoms) through the commonly used Cronbach's alpha, a statistical measurement between 0 and 1, that can check the internal consistency among the survey items, and help us know how closely related the items are as a group in relation to a latent variable (Mohsen Tavakol & Dennick, 2011). A Cronbach's alpha generates a reliability coefficient value between 0-1, where the generally accepted value ranges between .6 - .8 or above (Mohsen Tavakol & Dennick, 2011). Because our study is only concerned with the survey items' relationship to the latent trait of 'depression' and this has already been studied previously, instead of running our own Cronbach's alpha, we instead refer to Parbst & Wheaton's (2023) Cronbach's alpha analysis of 'depression' between the same CES-D 8 questions in the same ESS rounds, which was found to be .84 (p. 5). These findings fall within the acceptable range, and thus these questions as an index can be treated as a reliable and consistent measurement of the latent trait of 'depression' (Mohsen Tavakol & Dennick, 2011).

As an individual scores higher on the CES-D 8, the more intense depressive symptoms they exhibit, and the more likely they are to be experiencing major depressive disorder (American Psychiatric Association, 1994). For our single dependent variable, we take an averaged additive index of the 8 questions to give us *an average score for each individual from 8-32* in a departure from the CES-D 8 normal scoring rules (American Psychiatric Association, 1994). We make this numerical change in our study, due to the ESS survey tool measuring these depressive symptoms on a scale of 1-4. Thus, it is easier to interpret an individual's minimum score of 1 in the ESS survey questions instead of attempting to change them to zero's to mirror the CES-D 8. In measuring the latent construct of depression through our additive index score of depressive symptoms, we cannot use the original CES-D 8 scoring range of 0-24, and instead, opt for a scoring range of 8-32. This means for the purpose of our research, an additive score of 8 becomes the *minimum score*.

3.1.2 Independent Variables

Our independent variables in this study come from our country-specific OECD SOCX database which contains different social expenditure categories grouped by policy field of the related programs (OECD, 2023). We have chosen to conduct our analysis on both aggregated independent variable groups and some of the disaggregated independent variable within these groups because of previous research using social expenditure data that has shown that social protection policies are co-contributive in their effect (O'Campo et al., 2015; Niedzwiedz et al., 2016). We also choose to use both aggregated/disaggregated variables because limiting the analysis to a single program or aggregated group of programs runs the risk of missing causal impacts of other programs the state provides in tandem or that are directly related to protective service provision together (Niedzwiedz et al., 2016). We choose this method because our research focus is again on the effects of spending level *variance* in social protection policies on specific population groups, and thus the more variables we can include that depict this spending variance in one analysis of association, the better (Huntington-Klein, 2021; Parbst & Wheaton, 2023).

We have decided that the best way to test our hypotheses and answer our research question is to have 3 aggregated variable groups and 5 disaggregated independent variables (some of which are a combination of two disaggregated variables themselves). These 3 larger aggregate groups we call *Total Social Expenditure (T.S.E), Family Policy Related Programs (F.P.R.P.), and Old-Age + Incapacity-Related Programs (O.A. + I.R.P.).* These 3 aggregates make our first three independent variables (IV#1/IV#2/IV#3). Our disaggregated social policy spending program categories are Incapacity-Related Programs (cash benefits and in-kind benefits), Old-Age Programs (cash benefits and in-kind benefits), Survivors Total Benefits (cash benefits and in-kind benefits), Family Programs (Cash Benefits), and Family Programs (In-Kind Benefits). These 5 disaggregated variables are our independent variable #4 through #8 (IV#4/IV#5/IV#6/IV#7/IV#8). Please note that these 5 disaggregated variables are, however, still all combinations of many social policy programs, they are referred to as disaggregated variables because they are components we aggregate into our larger variable groups that comprise our first three independent variables. We are including the three aggregate groupings by type of spending that we hypothesize are likely to have an effect on individual depressive symptoms of specific populations (parents and those over age 65 specifically), and that are either understudied or have not been researched at all in regards to their relationship with individual depressive symptoms. We list aggregate variable groups that each represent one independent variable, and the disaggregated variables that represent an independent variable (these are labeled correspondingly) in the table below:

Table 4 - Independent Variables by Variable Group & Disaggregated Variables

Aggregated Variable Group	Disaggregated Variables
IV#1: *Total Social Expenditure (T.S.E)*	Active Labor Market Programs Unemployment Total Benefits Housing Total Benefits Other Cash+In-Kind Benefits All Family Policy Related Programs (F.P.R.P.) All Old-Age + Incapacity-Related Programs
IV#2: *Family Policy-Related Programs (F.P.R.P.)*	**IV#7:** Family Programs (Cash Benefits) **IV#8:** Family Programs (In-Kind Benefits)
IV#3: *Old-Age + Incapacity-Related Programs (O.A. + I.R.P.)*	**IV#4:** Incapacity-Related Programs (Cash + In-Kind) **IV#5:** Old-Age Programs (Cash + In-Kind) **IV#6:** Survivors Total Benefits (Cash + In-Kind)

(OECD SOCX Database, 2023)
Own Elaboration

As one can see, our first independent variable is an aggregate independent variable that is a combination of active labor market program spending, unemployment program spending, housing program spending, misc social policy program spending, and the other two aggregated variable groups listed in the table (F.P.R.P. 's and O.A. + I.R.P.'s.). Our next two aggregated independent variable groupings are family policy-related programs (F.P.R.P.), and old-age + incapacity-related programs (O.A. + I.R.P.). Notice that our 'O.A. + I.R.P.' independent variable group includes survivors' social protection benefits, a category that is often combined with old-age social protection program spending in the SOCX database, and one which we have chosen to include as a primarily old-age type of social program spending, due the programs being mostly utilized for those over 65. As we discussed above and labeled in the table, our other 5 independent variables (IV's #4-8) are portions of our larger variable groupings. We choose to run an analysis on these portions independently of their larger policy groups in the hope of gaining greater insight into associations that specific parts of the group may have with depressive symptoms in our chosen sample populations. This also allows us to see what part of the aggregate variable groups may constitute a larger effective part, ie. which combination of policies may have the most causal explanation for depressive symptom outcomes in a population.

Our categorization of aggregated social protection expenditure group variables follows research done by Kuitto (2016), who measured an aggregate variable of *social protection spending* as a combination variable of spending on incapacity, old age, survivors, and unemployment(Kuitto, 2016, as cited in Parbst & Wheaton, 2023). Other scholars have similarly used variations of this type of social protection program grouping to highlight types of social expenditure that may work for a certain population or provide outsized hypothesized benefits in certain areas specifically (Adema & Ladaique, 2005; Parbst & Wheaton, 2023). In our Total Social Expenditure (T.S.E.) variable, you can see we also include spending on housing programs, following previously discussed research done by Costa-Font (2008) on mental health inequality amongst older individuals 65+, who found that housing equity was a critical factor in income maintenance among this population, and thus we include it in our total spending analysis due to its effects on poverty and income maintenance. Critically, all of our social protection spending variables *include* "in-kind" benefit spending. In-kind social protection expenditure is expenditure or programs that provide recipients with non-cash benefits of monetary value and have not been counted often in other research that groups social protection spending variables (Kuitto, 2016; Parbst and Wheaton, 2023). However, we contend that this type of spending is important to include especially when looking at the relationship between mental health (depressive symptoms) and social protection expenditure because it provides large benefits to recipients that may impact mood, life satisfaction, and economic maintenance. The exclusion of in-kind benefits from the analysis is counterproductive for the purposes of our research because in-kind benefits consist of a core part of the government's social protection expenditure.

All of our 8 independent variables are measured at % of gross domestic product (GDP), both for ease of analysis and discussion. The % of GDP measurement is done by yearly GDP statistics and is used by other researchers in social expenditure approaches (O'Campo et al., 2015; Dahl et al., 2012; Kuitto, 2016; Parbst & Wheaton, 2023). Each of these independent variables is matched with different sample populations for our analysis, and the larger aggregate variable groups (IV#1-3) are matched with all of our three samples. As we will discuss in our next section, Methods, we run a fixed effect regression across 16 countries for all eight of our independent variables, and some of our independent variables are analyzed using a fixed effects regression model across multiple samples.

3.2 Method

3.2.1 Research Design

This study will contain a three-round empirical analysis in order to answer our research question and test our three hypotheses. Each round will consist of multiple fixed effect regressions (FE) and analysis conducted for our dependent variable ('depression' as measured by depressive symptoms) and independent variable (social policy spending group) pairing. Specifically, this study runs fixed-effects regressions to determine if associations are significant within countries between social policy program expenditure level and depressive symptom score. Round one of our analysis will comprise 5 fixed effects regression analyses focused on the within-country associations between shifts in family policy related social expenditure independent variables and depressive symptom outcomes. Round two focuses on investigating the within-country associations between shifts in old-age and incapacity-related social expenditure independent variables and depressive symptom outcomes through 6 fixed effects regressions. Round three will be our final three fixed-effects regressions, looking at any association between shifts in total social expenditure amounts and depressive symptom outcomes.

We create a coefficient for analysis for all of our countries' depressive symptom outcome scores and social policy spending group pairing by running 14 separate fixed-effects regressions with our 3 different samples and 8 different independent variables (S#1/S#2/S#3 & IV#1-8). We pair specific samples with different independent variable groups according to the theme of the independent variable, while also analyzing cross-over associations between the larger social policy spending group variables (IV's #1-3) and all three of our samples. In the table below, one can see the different independent variables and sample pairings, as well as the total number of regressions that result from each group of pairings.

Table 5 - Independent and Dependent Variable Interactions by Sample Group

Sample (Dependent Variable = Depressive Symptoms)	**Independent Variables**	**Total # of Regressions**
Sample #1: Parents Sample (N = 30064)	**IV#1:** Total Social Expenditure **IV#2:** Family Policy Related Programs **IV#3:** Old-Age + Incapacity-Related Programs **IV#7:**Family Programs (Cash Benefits) **IV#8:** Family Programs (In-Kind Benefits)	**5 Fixed Effects Regressions**
Sample #2: Age 65+ Sample (N = 21309)	**IV#1:** Total Social Expenditure **IV#2:** Family Policy Related Programs **IV#3:** Old-Age + Incapacity-Related Programs **IV#4:** Incapacity-Related Programs (Cash + In-Kind) **IV#5:** Old-Age Programs (Cash + In-Kind) **IV#6:** Survivors Total Benefits (Cash + In-Kind)	**6 Fixed Effects Regressions**
Sample #3: Total Sample (N = 91859)	**IV#1:** Total Social Expenditure **IV#2:** Family Policy Related Programs **IV#3:** Old-Age + Incapacity-Related Programs	**3 Fixed Effects Regressions**

As each sample is defined by a characteristic (those over age 65 or those who have ever been parents or guardians of children), we pair social policy spending independent variables with specific samples because we have hypothesized that these categories are likely to have an impact on that population's depressive symptoms. As discussed previously, we also test the disaggregate variables with their corresponding sample group based on the similar idea of looking for likely associations but with the added idea of also attempting to look within the black box of social policy spending groupings and see if specific policy categories have stand-out associations with depressive symptoms (e.g. family programs both cash and in-kind benefits which are IV#7 and IV#8 are paired with Sample #1: Parents Sample). Finally, we test our major aggregate independent variables (IV's #1-3) across all three samples, as this can contextualize if associations seen between specific independent variables and samples are more generalizable across different or larger populations, or if they are specific to that population. All computations are done using RStudio, an integrated development environment for R, a programming language for statistical computing and graphics. All models use ESS post-stratification weight.

3.2.2 Regression Models & Fixed Effects

In total, this study presents and analyzes 14 fixed effects regressions. Regression models describe relationships between independent and dependent variables, and they are used as a common way to identify causal effects by estimating the relationship between two variables while controlling for others (Huntington-Klein, 2021). With our ESS panel data, multiple rounds of regression analysis will illuminate the meaningful associations and correlations between our independent and dependent variables across units and time (Huntington-Klein, 2021). We choose to use a fixed-effects regression model because of our research question's focus on how changes in the social spending level *within* a country can impact that same country's individual depressive score outcome. Each fixed effects regression gives us a look at the relationship of *within* effects, e.g. the relationship between change in social program spending levels within a country, and the changing level of individual depressive symptoms within that same country (Huntington-Klein, 2021). This is because fixed effects models, unlike standard linear regression models, control for an entire categorical variable (in our studies case the categorical variable is country), and thus we effectively remove any variation between the individuals (Huntington-Klein, 2021). It is critical to understand what we mean by our methodological focus on *within* variation and not *between* variations. Our model of regression, a fixed-effects model, cannot be used to look at the difference between individuals in the means (Arnold, 2020). To understand why, let's say for example we want to compare differences in Belgium's family policy program spending/mean depression score and Norway's family policy program spending/mean depression score. We wouldn't want to control for the entire country as a categorical variable, because we want to compare the different countries. In a fixed effects model, instead, we are controlling for the individual (country) as a categorical variable, and by applying a fixed effects model we are only left with the variation within the variable we control for itself, ie. our fixed effects model allows us to compare the variable to itself over time (Huntington-Klein, 2021). This is why our fixed-effects model gives us a valuable look at an estimation of the effect of a variable (in this case social policy expenditure level) on another variable (depressive symptoms) within units (our 16 countries) over time (our three ESS round years) (Arnold, 2020; Huntington-Klein, 2021). In this study, we are only interested in the within-country variation, because our research question is asking if government changes in social policy spending over time in that same government affect depressive symptom outcomes of a variety of populations.

3.2.3 Regression Estimator

We chose to use a specific type of regression model, a fixed effects regression estimator because this type of estimator is commonly used by researchers to estimate causal effects in panel data (in this case the data we are using from the three ESS survey rounds: 2006, 2012, and 2014) and is used to "adjust for unobserved unit-specific confounders at the same time" (Imai & Kim, 2021, p. 1). A fixed effects regression is particularly useful for our analysis, as it will control for all confounding variables, whether they're observed or not, as long as they stay constant within some larger category (Huntington-Klein, 2021). This allows us to just control for the larger category, in our case, we are controlling for unit (country) (Huntington-Klein, 2021). We are using a fixed effects regression estimator in our study because we are investigating social expenditure data and ESS panel data that spans 3 distinct time periods and is unit-specific to each European country we include in our study (16 countries). Unlike other research done on inequality in depression outcomes and social spending's mediating effects, we *DO* control for GDP and every other unobserved country-specific confounding variable (Niedzwiedz et al., 2016). We do this because *without* controlling for the entire unit, we would allow large confounders (such as GDP, or healthcare spending/system type) into our estimations that may obfuscate the causal effect of only social policy program spending on depressive symptom outcomes.

Now, we explain our regression estimator in detail. Consider the following panel regression model (Arnold, 2020):

$$Yi = \beta 0 + \beta 1Xi + \beta 2Zi + \varrho i$$

In this panel regression model, Zi are the unobserved time-invariant heterogeneities across the entities $i = 1,\ldots n$ (Arnold, 2020). Because our goal in this study is to estimate the effect $\beta 1$(or a combination of β up to n units), which is the effect of a change in Xi, our binary treatment indicator, on Yi, the observed outcome variable, holding constant Zi, we can let $\alpha i = \beta 0 + \beta 2Zi$ (Arnold, 2020).

From this, we obtain our fixed effects model:

$$Yi = \beta 1X1i + \ldots + \beta n\ Xni + \alpha i + \varrho i$$

This model is very similar to what we will be using in our analysis, but we will be inserting new independent and dependent variables into it during different rounds of analysis. The equation can be understood as ***Yi*** = observed outcome variable (the dependent variable) which will be our CES-D 8 survey questionnaire score (an aggregate value that represents the combination value of all 8 question responses) for unit *i* (Arnold, 2020; Imai & Kim, 2021). ***Xi*** = our binary treatment indicator (the independent variable) for unit *i*, which in our study will be different social expenditure amounts/groupings across the rounds of analysis, e.g. the family policy program spending group expenditure amount (Arnold, 2020; Imai & Kim, 2021). Furthermore, in this model, ***αi*** represents the unit fixed effects. We can understand ***αi*** as individual specific intercepts, ***i*** = 1,...***n (i*** being each of our 16 countries with one country representing a constant). Again, ***αi*** represents our controls, as it represents our unobserved time-invariant heterogeneity across entities (which in the panel model was ***Zi***). That is to say, ***αi*** variation comes from the fact that it contains Zi (the fixed effect we hold constant) (Arnold, 2020). The ***ϱi*** represents our error term (or residual disturbance), which represents the amount of error distance that separates this model from the actual reality, with the ***αi*** fixed effects applied (Huntington-Klein, 2021). The error term includes nonlinearities and unpredictable effects, as well as measurement errors (Wooldridge, 2021; Huntington-Klein, 2021).

3.3 Limitations & Validity

There are many limitations to this study due to our choice of method and because of the type of data we employ. The independent and dependent variables chosen for this study have been selected due to their theoretical relevance, based on prior research and empirical background. However, there is always a risk of omitted variable bias, i.e., the exclusion of significant explanatory (independent) variables (Huntington-Klein, 2021). While we hope to narrow this down through the use of fixed effects regression models in order to ascertain causal effects, our choice of the method also means we lose the ability to analyze any important explanatory *between*-country effects that spending amount or type or structure may have on depressive symptoms (Parbst & Wheaton, 2023). Our choice of method only allows us to analyze any within-country associations. Also, due to how fixed effects are calculated with a focus on within variation, the treatment effect of our independent variables (spending amounts) that we estimate focuses more heavily on countries that in our three years of data have a lot of variation in spending level (Huntington-Klein, 2021). For example, our estimations will skew with countries that have a lot of variation in % of GDP spent on different social protection policy programs over the 3 years we use in our analysis specifically (2006, 2012, 2014). Countries in these 3 years that don't have a lot of variance in their spending numbers won't have as close an estimator as to its effect. This is the major drawback in fixed effects estimators and a serious limitation to our results. However, we still feel this method is more valid to ascertain the true treatment effects of spending level changes on depressive symptoms than to run simple linear regressions as previous research into this topic has done without controlling for major confounders such as GDP (Niedzwiedz et al., 2016). Without controls, other confounders are likely to be present but less obvious. The problem of outlier countries affecting the results of our research due to our small sample size of countries observed (16) can be an issue, skewing our estimators (Van der Meer et al., 2010). The use of diagnostic tools may have helped identify and exclude obvious outlier countries.

Furthermore, our study has clear limitations in terms of generalizability. We cannot make any claims following our research about specific groups of a country’s population that may be affected in an outsized way in terms of their mental health by certain types of social expenditure (ie. unemployed individuals as we do not segregate based on employment status). We also don’t have any way to zoom in on the educational status of respondents, marital status, income, and many other socio-demographic factors that could shed light on the variety of mental health impacts of non-health-related social expenditure. This study only holds validity in the macro-level for each respondent country. In this sense, we can only make claims about the relevance of non-health-related social expenditure towards aggregate groupings of a country's population (such as parents or those over age 65) but we cannot understand what part of that group may be most impacted or not impacted at all. We thus have no ability in this study to see the variance of the impact that social protection expenditure may have inside of our sample. We also cannot necessarily generalize our findings anywhere outside of the 16 countries in this analysis. However, our findings hold strong across the European context due to our large sampling of European country contexts.

Nevertheless, our ESS rounds when combining countries contain large sample sizes, and our use of post-stratification weight in our statistical analysis with the ESS data across rounds begets the validity of our samples. Our CES-D 8 measurement tool has been generalized for European country contexts as a valid measure of depression, and other research has used it across different analyses, with a recent paper finding a Cronbach’s alpha of the latent trait ‘depression’ between the 8 questions to be .84, a very valid score (Van de Velde et al., 2009; Parbst & Wheaton, 2023).

4. Results & Analysis

4.1 Description of Sample

In our statistical analysis, we first examine the descriptive statistics for each sample, including the means of our CES-D 8 scores to see the general occurrence of depressive symptoms by unit over time, and we look at trends in government social policy expenditure by the sample over time.

In the table below, we can see the aggregated mean depressive symptom scores for all individuals across all three ESS rounds (2006, 2012, and 2014) in each of our three samples, Sample #1: Parents, Sample #2: Age 65+, and Sample #3: Total. We can also see the average means of depression by ESS Round, and thus over time. The Sample depressive symptom means are an average depressive symptom score over all three years (the three columns on the right of the table) while the ESS depressive symptom means are the mean scores of depressive symptoms by the sample in each ESS Round, and thus by time (the three columns on the left). One can see the full disaggregated depressive symptom mean scores for each country both over time and in each ESS Round in Appendices A and B.

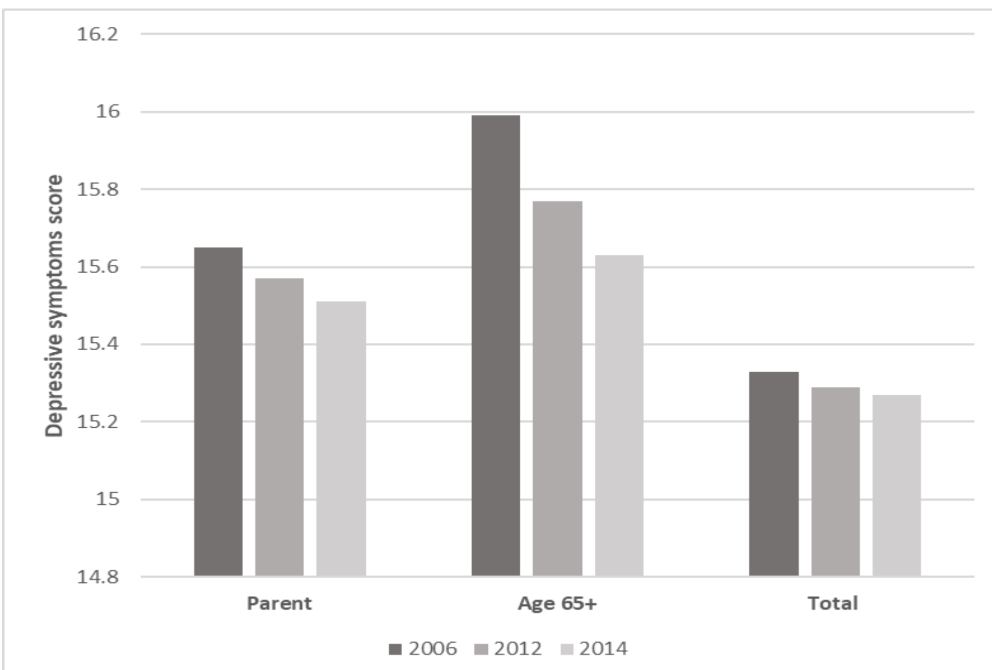
Table 6 - Aggregated Means of Depression by Sample Type and ESS Round

Depression (Mean)											
ESS Round 3 (2006)			***ESS Round 6 (2012)***			***ESS Round 7 (2014)***			***Total Mean Depression Score Over All ESS Rounds***		
Parent	**Age 65+**	**Total**	**Parent**	**Age 65+**	**Total**	**Parent**	**Age 65+**	**Total**	***Sample #1: Parents***	***Sample #2: Age 65+***	***Sample #3: Total***
15.65	**15.99**	**15.33**	**15.57**	**15.77**	**15.29**	**15.51**	**15.63**	**15.27**	**15.53**	**15.78**	**15.30**
Range: 8-32											

If we first look at the total mean depression scores over time (the three columns on the right), we can see that the population of S#1, our parents' sample, are on average showing fewer depressive symptoms than our older population over our three years of data. Interestingly, both of our targeted populations, S#1 and S#2 show a higher average depressive symptom score than our total population, S#3. The variance between our samples in depressive symptom scores is not necessarily large, as all populations score within one point of each other, but the variance between the mean depressive symptom scores of our sample populations is present nevertheless. The mean depressive symptom scores of our S#1 and S#2 being higher than the average score of our total population fit within our previous theoretical justification for our hypotheses. As we previously noted, our targeted populations, parents and those over age 65, tend to have specific economic stressors and immediate needs that the government social policy programs address that others in the total population do not have (such need for and increased use of disability income replacement, healthcare benefits, pension, child care, and other specific social safety programs). This led us to believe that these populations might be particularly affected by changes in social policy program expenditure levels. While we cannot conclude anything from the depressive symptom means of each sample over time, we can see that each sample population has variance in their average depressive symptom score and that the total population is on average less depressed than our specific targeted populations of those over 65 and those who are or have been parents or guardians of children.

If we view the columns on the left of this table, looking at mean depressive score variation over time by ESS round, we can see that again variance between our depression means across samples is present, but is not beyond 1 point either way. We can also see that the mean depression score for each sample is decreasing from 2006 to 2014. If we look at the graph below, we can see a visual representation of our depression means for each sample across time. It is immediately apparent that the aggregate countries' mean depression scores for ALL of our samples are falling over time. In other words, our sample populations are showing fewer depressive symptoms over the time covered in our data, 2006, 2012, and 2014, with depression falling mildly from 2006 to 2014 in all three of our samples. Our population's depressive symptom scores fall most rapidly over time amongst our Age 65+ population.

Graph 1 - Aggregate Mean Depressive Symptoms by Sample Type over Time



In our next table, we can see all of the government expenditure levels of our three large aggregated independent variables (IV's #1-3) over different ESS rounds.

Table 7 - Within Country Descriptives of Family Policy Program, Old-Age + Incapacity-Related Program, and Total Public Social Protection Program Expenditure in % of total Gross Domestic Product (GDP)

	ESS Round 3 (2006)			**ESS Round 6 (2012)**			**ESS Round 7 (2014)**		
Country	**O.A. + I.R.P.**	**Family P.R.P.**	**Total S.P.E.**	**O.A. + I.R.P.**	**Family P.R.P.**	**Total S.P.E.**	**O.A. + I.R.P.**	**Family P.R.P.**	**Total S.P.E.**
Belgium	11.1	2.6	24.6	13	2.8	28	13.4	2.9	28.4
Denmark	12.7	3.5	25	15.2	3.8	30.2	15.1	3.6	30
Estonia	7	1.7	12.4	8.7	2	15.8	8.6	2.3	16
Finland	12.6	2.8	23.8	15.4	3.2	28.3	16.5	3.2	30.2
France	13.8	2.8	28.4	15.7	2.9	31.2	16	3	32
Germany	12.7	1.7	25.1	12.3	2.2	24.7	12.1	2.2	24.8
Ireland	5.1	2.6	15.8	7.9	3.2	23	7.1	2.7	20.1
Netherlands	8	1.8	16.4	9.4	1.4	17.9	9.3	1.3	17.9
Norway	10.3	2.7	19.5	11.3	3	21.5	12.2	3.2	22.8
Poland	14.2	1.2	20.6	13.3	1.3	19.9	13.7	1.4	20.3
Portugal	12.5	1.2	21.6	14.9	1.2	24.3	15.8	1.2	25
Slovenia	12.2	1.9	21.1	13.5	2.1	23.5	13.5	1.8	23.1
Spain	10.8	1.2	20.5	13.4	1.3	25.6	14.2	1.3	25.4
Sweden	14.1	3.2	26.4	13.5	3.5	26.3	13.7	3.5	26.6
Switzerland	9.1	1.4	14.9	9.1	1.5	15.4	9.1	1.6	15.6
U.K.	7.4	2.8	19.1	8.8	3.9	23	8.3	3.5	21.7
Mean (% of Natl. GDP)	**10.85**	**2.19**	**20.95**	**12.21**	**2.46**	**23.66**	**12.41**	**2.42**	**23.74**

Overall, we can see that our total social protection expenditure by % of natl. GDP is rising from 2006 to 2012, to 2014. This rise in Total S.P.E. is non-trivial in its amount, from an average across all countries of 20.95% of GDP spent on social protection policy by ESS Round 3 (2006) to 23.66% by ESS Round 6 (2012), to 23.74% by ESS Round 7 (2014). Similarly, across all countries, O.A. + I.R.P. spending rose from an average spending level of 10.85% of GDP in 2006 to 12.21% in 2012, followed by a rise to 12.41% in 2014. Our only spending level that has a decrease is Family P.R.P. spending, which falls a slight amount from an average of 2.46% of GDP in 2012 to 2.42% of GDP in 2014. This decrease in the average expenditure level of Family P.R.P. spending between these two rounds is the only spending level decrease found in the aggregate for our three large-grouped social protection spending variables. It also follows a rise in the average Family P.R.P. spending of 2.19% of GDP to 2.46% from 2006 to 2012.

We can also see that a nontrivial amount of spending differences exists across groups of social policy expenditure, with Family P.R.P. spending being the lowest average % of GDP amount being spent across all of our 16 countries. Comparatively, countries spend more on O.A. + I.R.P. programs on average, with this package of policies making up half or nearly half of total spending each year on average across all countries.

If we take both our observations of our dependent variable for each sample, depressive symptoms, and our independent variables, social protection spending, we can identify two major trends regarding our variables across our data. First, social policy program spending is increasing over time on average across almost all of our independent variable spending groups with non-trivial increases. Even taking our 2012 to 2014 decrease in average Family P.R.P. spending, 2014 average spending on Family P.R.P. is still larger than the 2006 average spending on Family P.R.P. Second, our sample populations are becoming less depressed via a reduction in depressive symptoms over time from 2006 to 2014 on average across ALL of our samples, with the biggest reductions in depressive symptom scores over time being in the Age 65+ sample.

4.2 Fixed-Effects Regression Analysis Results

Now I present the results from the 14 fixed-effects (FE) regressions that have been run across our three samples and our 8 independent variables. I have run the 8 independent variables in separations across our three samples, with sample one including 5 independent variables, sample two containing 6 independent variables, and sample 3 concerning 3 independent variables, which results in 14 FE regressions. Although we present our regression's results in this chapter, we comment on our different independent variables (expenditure groups of social policies) explanatory power in relation to our dependent variable (depressive symptom score) as it pertains to our research question and hypotheses in more depth and detail in our following chapter, Discussion & Conclusion. Now, we examine the three-round analysis of the three different samples, S#1: Parents Sample, S#2: Age 65+ Sample, and S#3: Total Sample, and their interactions with our different independent variables IV's #1-8.

In the tables that contain the results presented below, I have made it so each column represents an independent variable, and each row pertains to either a fixed component such as the regression's intercept, or a country binary variable. One will notice that the same country, Belgium, is missing from each table, and this is because Belgium is stuck in the model as the constant (even as its within-country estimator is included in the larger focal association estimator that is created from each fixed effects regression). While not the main focus of this study, the presented fixed component, country coefficients, that are created from each fixed-effects regression are included in the presentation of the results because they can actually be used to make interesting claims about the countries themselves that we have controlled for in our fixed effects regressions (Huntington-Klein, 2021). While we can rarely think of these unit fixed effects (our country coefficients) as causal, they serve as an intriguing look into the countries being analyzed in terms of their depressive symptoms in relation to their levels of social policy expenditure by grouping (Huntington-Klein, 2021). In the second row of each table, one can find the main focal association that this study concerns itself with, which is the expenditure level of each independent variable grouping on depressive symptoms in all of our countries. FE regression coefficients and country coefficients are highlighted in bold for each FE regression's focal association and related fixed components (country coefficients, intercept, etc.). Standard errors are given in parentheses, and t-statistics are given in brackets.

4.2.1 Round One: Sample #1: Parents Sample

Table 8 - Sample #1 Within-Country Fixed Effects of Social Policy Pooled Expenditure on Depressive Symptoms (N = 30064)

	IV#1: Total S.P.E.	**IV#2: Family P.R.P.**	**IV#3: O.A.+ I.R.P.**	**IV#7: Family Cash**	**IV#8: Family In-Kind**
Focal Association: Expenditure Level	**-0.0368249 **** (0.0141502) [-2.602]	**-0.021460** (0.012043) [-1.782]	**-0.026038 *** (0.012483) [-2.086]	**-0.042370 *** (0.017786) [-2.382]	**-0.015214 *** (0.005946) [-2.559]
Fixed Components					
Intercept	**2.8600505 ***** (0.0468766) [61.012]	**2.760491 ***** (0.013081) [211.028]	**2.804419 ***** (0.031865) [88.010]	**2.762949 ***** (0.011173) [247.295]	**2.738303 ***** (0.004542) [602.895]
Country Coefficients					
Switzerland	**-0.0502490 ***** (0.0104117) [-4.826]	**-0.042544 ***** (0.009962) [-4.271]	**-0.037408 ***** (0.007634) [-4.900]	**-0.046962 ***** (0.009929) [-4.730]	**-0.045618 ***** (0.009169) [-4.975]
Germany	**-0.0409347 ***** (0.0056594) [-7.233]	**-0.044531 ***** (0.006686) [-6.660]	**-0.038173 ***** (0.005536) [-6.896]	**-0.056984***** (0.009756) [-5.841]	**-0.039006 ***** (0.005552) [-7.026]
Denmark	**-0.0519686 ***** (0.0061940) [-8.390]	**-0.047809 ***** (0.006974) [-6.855]	**-0.050186 ***** (0.006379) [-7.868]	**-0.063227***** (0.007361) [-8.589]	**-0.041272 ***** (0.007829) [-5.272]
Estonia	**0.0122100** (0.0101364) [1.205]	**0.027091 ***** (0.006950) [3.898]	**0.022940 **** (0.007820) [2.933]	**0.027928 ***** (0.006356) [4.394]	**0.022669 *** (0.007289) [3.110]
Spain	**0.0148577 *** (0.0070984) [2.093]	**0.002740** (0.011649) [0.235]	**0.020087 **** (0.006877) [2.921]	**-0.035210** (0.023973) [-1.469]	**0.015771 *** (0.007024) [2.245]
Finland	**-0.0699745 ***** (0.0057646) [-12.139]	**-0.068176 ***** (0.005889) [-11.577]	**-0.066061 ***** (0.006116) [-10.801]	**-0.077398***** (0.006482) [-11.941]	**-0.063474 ***** 0.006356 [-9.987]
France	**0.0106594** (0.0060572) [1.760]	**0.007122** (0.005828) [1.222]	**0.011186** (0.006288) [1.779]	**0.001904** (0.006066) [0.314]	**0.010484** 0.006046 [1.734]
United Kingdom	**-0.0004034** (0.0066020) [-0.061]	**0.012752 *** (0.006164) [2.069]	**-0.002670** (0.007770) [-0.344]	**0.017778**** (0.006893) [2.579]	**0.010991** (0.005753) [1.911]

Ireland	**-0.0291417 ***** (0.0075100) [-3.880]	**-0.017682 **** (0.006304) [-2.805]	**-0.033814 ***** (0.009682) [-3.492]	**-0.010739** 0.007075 [-1.518]	**-0.023475 ***** (0.006587) [-3.564]
Netherlands	**-0.0311936 ***** (0.0086634) [-3.601]	**-0.028647 **** (0.009737) [-2.942]	**-0.023838 **** (0.007371) [-3.234]	**-0.059014 **** (0.019421) [-3.039]	**-0.018227 **** (0.006174) [-2.952]
Norway	**-0.0857055 ***** (0.0072116) [-11.884]	**-0.075314 ***** (0.006361) [-11.840]	**-0.079548 ***** (0.006468) [-12.299]	**-0.088540***** (0.008051) [-10.998]	**-0.069202 ***** (0.006955) [-9.950]
Poland	**0.0553314 ***** (0.0081356) [6.801]	**0.049910 ***** (0.011455) [4.357]	**0.068334 ***** (0.007104) [9.620]	**0.026770** (0.017918) [1.494]	**0.058426 ***** (0.007623) [7.664]
Portugal	**0.0518105 ***** (0.0061745) [8.391]	**0.039512 ***** (0.011613) [3.402]	**0.060282 ***** (0.005937) [10.154]	**0.020819** (0.016432) [1.267]	**0.045780 ***** (0.007366) [6.215]
Sweden	**-0.0620395 ***** (0.0059677) [-10.396]	**-0.056833 ***** (0.006446) [-8.817]	**-0.058718 ***** (0.006078) [-9.661]	**-0.070683 ***** (0.007165) [-9.866]	**-0.050424 ***** (0.007299) [-6.908]
Slovenia	**-0.0002501** (0.0075729) [-0.033]	**-0.001446** (0.008350) [-0.173]	**0.007483 ***** (0.007176) [1.043]	**-0.004061** (0.008356) [-0.486]	**-0.050424 **** (0.007299) [-6.908]

Note: Robust standard errors in (parentheses) and t-statistics in [square brackets]. Data are from Rounds 3, 6, and 7 of the European Social Survey and the OECD SOCX database. Belgium is treated as the constant in the fixed effect regressions.
*** p<0.01, ** p<0.05, * p<0.1

In the first round of fixed effects regressions for Sample #1: Parents Sample (N = 30064), we can immediately focus on the most interesting part of our results, which are the coefficients presented in our focal associations: expenditure level (row 2). For the purposes of the analysis, we are interested in both statistically significant and insignificant coefficients as they offer answers as to which independent variables, and thus expenditure levels of groups of social policies, may carry causal power in relation to depressive symptoms of the sample population across different countries. The analysis of all coefficients in this table and all those that will follow can be generally explained as, within the same value of the unit (country), how is the variation in expenditure level of Total S.P.E. social policy group related to variation in depressive symptom score? (Arnold, 2020).

Looking at the coefficient for IV#1: Total Social Protection Spending (S.P.E.), we see that it is (-0.0368249***). It is a negative value, statistically significant with a p-value under 0.05. Substantively, this indicates that for a given unit (in this case country), in a year where Total S.P.E. is one unit higher than it typically is for that unit (country), we can expect the 'Depression' score (the combination of 8 survey questions on depressive symptoms, range 8-32) to be -0.036 points lower than it would typically be for that country. In other words, Total S.P.E. has a statistically significant ***inverse*** relationship with depressive symptom-dependent value in Sample #1: Parents Sample population (N = 30064). Although this inverse relationship between IV#1: Total S.P.E. and depressive symptom score is statistically significant, it is a very small effect considering the range of depressive symptom scores is from 8 to 32.

Now let's turn to the country coefficients (our fixed effects) for column one (IV#1). While these cannot be used to make any casual statements in any certain way, they make sense relative to each other, and we can use them to consider a sort of opposite effect, where the unit (country) controls expenditure level (Huntington-Klein, 2021). Each of these coefficients represents an intercept for that country that makes sense in relation to other countries' intercepts. Take Norway's statistically significant coefficient of (-0.0857055***), the lowest of the whole FE regression. If we consider Norway's coefficient with Ireland's statistically significant coefficient of (-0.0291417***), we can see Norway's intercept is lower than Ireland's. This can be interpreted to mean that if Norway and Ireland had the same expenditure level for IV#1, Norway's average depressive symptom score would be lower than Ireland's. An analysis of the country's coefficient difference would be that given Norway's level of total social protection expenditure, it has, especially low depressive symptom scores. Again, while statistically significant, the effect of IV#1, total S.P.E. levels on depressive symptom score altogether is very low considering the range of scores is 8-32.

Moving on from IV#1: Total S.P.E., we can look at the association between IV#2: Family P.R.P. spending levels and depressive symptom scores in the sample of parents (S#1). Surprisingly, we find a statistically insignificant negative coefficient (-0.021460) for the association between Family P.R.P. spending and the depressive symptoms of the population of the S#2: Parents Sample. This result contradicts a central hypothesis of this study, and we discuss why and the significance of this result in the next chapter. Looking at the most extreme fixed effect country coefficients, we see again Norway (-0.075314***) has the highest statistically significant negative coefficient, while Estonia has a *positive* coefficient of (0.027091***) which is also statistically significant. Thus given the same level of Family P.R.P. spending, we could expect Estonia to have a *significantly higher* mean depressive symptom score than Norway, which may point to these individual (unit) fixed effects perhaps being influenced by some unobserved time-varying variables that are confounding any true causal associations (Huntington-Klein, 2021).

Turning to IV#3: Old-Age + Incapacity-Related Program spending, we find a statistically significant (p-value < 0.1) coefficient of (-0.026038*) for the association between IV#3: O.A. + I.R.P. and the depressive symptoms of the parents' sample. While the inverse relationship between IV#3 and the depressive symptom score of Sample #1 is lower than IV#1, it is still a statistically significant inverse relationship between Old-Age + Incapacity-Related Program spending and depressive symptom scores over Sample #1's population of parents.

Looking at IV#7: Family Cash Benefits and IV#8: Family In-Kind Benefits, the results show coefficients of (-0.042370*) for IV#7: Family Cash Benefits and (-0.015214*) for IV#8: Family In-Kind Benefits. Both coefficients are negative, and significant at p-values of < 0.1. Of particular interest is that the coefficient for IV#7, -0.042370*, is the largest significant effect we observe in all 5 of the fixed effect regressions between IV's #1, 2, 3, 7, 8, and the Sample #1: Parents Sample depressive symptoms dependent variable. Both IV#7 and IV#8 estimators are negative and significantly associated with Sample #1 depressive symptom outcomes, and thus show an inverse relationship between increases in their specific expenditure levels over time and Sample #1 depressive symptom outcomes. This is intriguing because IV#7 and IV#8 are the disaggregate components of our grouped expenditure variable Family P.R.P. (IV#2), which when interacted with Sample #1 as its own independent variable resulted in an insignificant positive association between expenditure level and depressive symptoms. Overall, we find 4 out of 5 fixed effects regression coefficients estimating the relationship between IV#1, 2, 3, 7, 8 and Sample #1: Parents Sample to show an inverse relationship between increases in specific social policy expenditure level and sample populations' depressive symptoms. However, the main interaction fixed effects coefficients are small and the associative effect of within-country social policy program expenditure level and sample population depressive symptom outcomes is minor when contextualized by the CES-D 8 depression score for individuals ranging from 8-32.

4.2.2 Round Two: Sample #2: Age 65+ Sample

Let us consider now round two of the results and analysis, concerning IV's #1, 2, 3, 4, 5, 6, and Sample #2: Age 65+ sample. Looking at the table below, one can see that the layout mirrors the previous table in round one, with obvious changes in the IV's we are examining, and the addition of a column on the right as this round contains six fixed effects regressions. The main focal association being examined remains the expenditure level's effect on the sample population's depressive symptom score. The first coefficient we encounter is for IV#1: Total S.P.E., (-0.076562***), and the value is negative and statistically significant at p-value < 0.01. It is also a considerably larger negative coefficient than any we have seen before, nearly 40% larger than the IV#7 largest negative significant expenditure level coefficient from Sample #1. This negative coefficient shows that there is a statistically significant inverse relationship within countries between increases in Total S.P.E. expenditure and decreases in CES-D 8 depressive symptom score of Sample #2: Age 65+ population. While again the coefficient shows that this inverse relationship is significant, it is not a very large effect. If one considers the CES-D 8 country aggregate depressive symptom score means that were presented earlier in the chapter, it can be noted that variance in mean depressive symptom score was always between 0-1 across all years and all samples.

Table 9 - Sample #2 Within-Country Fixed Effects of Social Policy Pooled Expenditure on Depressive Symptoms (N = 21309)

	IV#1: Total S.P.E.	**IV#2: Family P.R.P.**	**IV#3: O.A.+ I.R.P.**	**IV#4: I.R.P.**	**IV#5: O.A.**	**IV#6: Survivors**
Focal Association: Expenditure Level	**-0.076562 ***** (0.016331) [-4.688]	**-0.009803***** (0.006652) [-1.474]	**-0.055413 ***** (0.014260) [-3.886]	**0.014551** (0.015368) [0.947]	**-0.052014 ***** (0.011818) [-4.401]	**0.018870 **** (0.006038) [3.125]
Fixed Components						
Intercept	**2.995070 ***** (0.054085) [55.378]	**2.810112 ***** (0.015791) [177.952]	**2.882645 ***** (0.036396) [79.201]	**2.729334 ***** (0.015199) [179.575]	**2.862315 ***** (0.027691) [103.368]	**2.730575 ***** (0.006670) [409.399]
Country Coefficients						
Switzerland	**-0.073023 ***** (0.012095) [-6.038]	**-0.070352 ***** (0.011881) [-5.922]	**-0.046897 ***** 0.008944 -5.243	**-0.031024 ***** 0.007918 [-3.918]	**-0.053449 ***** (0.009464) [-5.648]	**-0.004116** (0.011189) [-0.368]
Germany	**-0.043863 ***** (0.006817) [-6.434]	**-0.058126 ***** (0.008072) [-7.201]	**-0.038158 ***** (0.006687) [-5.706]	**-0.033997 ***** (0.007693) [-4.419]	**-0.035411***** (0.006704) [-5.282]	**-0.038232 ***** (0.006690) [-5.715]
Denmark	**-0.047735 ***** (0.007810) [-6.112]	**-0.033673 ***** (0.008739) [-3.853]	**-0.044046 ***** (0.008020) [-5.492]	**-0.062510***** (0.013621) [-4.589]	**-0.056272***** (0.007823) [-7.193]	**0.039543** (0.030274) [1.306]
Estonia	**0.005325** (0.011968) [0.445]	**0.029696 ***** (0.008456) [3.512]	**0.027315 **** (0.009276) [2.945]	**0.053845 ***** (0.007970) [6.756]	**0.026022 *** (0.009022) [2.884]	**0.111667 ***** (0.020840) [5.358]
Spain	**0.015383 *** (0.007814) [1.969]	**-0.026564** (0.013654) [-1.946]	**0.026352 ***** (0.007542) [3.494]	**0.025627 ***** (0.007558) [3.391]	**0.026882***** (0.007545) [3.563]	**0.022275 **** (0.007590) [2.935]
Finland	**-0.059135 ***** (0.007077) [-8.356]	**-0.053776 ***** (0.007243) [-7.425]	**-0.050971 ***** (0.007523) [-6.775]	**-0.066760 ***** (0.009326) [-7.158]	**-0.054915***** (0.007200) [-7.627]	**-0.045538 ***** (0.008627) [-5.279]
France	**0.020513 **** (0.007508) [2.732]	**0.014005** (0.007249) [1.932]	**0.021833 **** (0.007758) [2.814]	**0.016728** (0.009587) [1.745]	**0.026856 ***** (0.008089) [3.320]	**0.013239** (0.007260) [1.824]
United Kingdom	**-0.012398** (0.007783) [-1.593]	**0.019290 **** (0.007389) [2.610]	**-0.017693** (0.009053) [-1.954]	**0.009183** (0.007689) [1.194]	**-0.019187 **** (0.008813) [-2.177]	**0.067407 **** (0.020864) [3.231]
Ireland	**-0.035893 ***** (0.008766) [-4.095]	**-0.009993** (0.007073) [-1.413]	**-0.046088 ***** (0.011352) [-4.060]	**-0.006959** (0.008580) [-0.811]	**-0.048932 ***** (0.011045) [-4.430]	**0.009773** (0.009826) [0.995]
Netherlands	**-0.047293 ***** (0.010158) [-4.656]	**-0.056044 ***** (0.011775) [-4.760]	**-0.032425 ***** (0.008673) [-3.739]	**-0.016209 *** (0.007637) [-2.122]	**-0.040322***** (0.009408) [-4.286]	**0.032451 *** (0.016527) [1.963]

Norway	**-0.092075** *** (0.009076) [-10.144]	**-0.069213** *** (0.008261) [-8.378]	**-0.079509** *** (0.008329) [-9.546]	**-0.080022** *** (0.010501) [-7.621]	**-0.089492** *** (0.008939) [-10.011]	**-0.036648** * (0.014445) [-2.537]
Poland	**0.086298** *** (0.009237) [9.342]	**0.058528** *** (0.013552) [4.319]	**0.113467** *** (0.008066) [14.067]	**0.108527** *** (0.007962) [13.630]	**0.114487*** (0.008078) [14.172]	**0.107800** *** (0.007959) [13.545]
Portugal	**0.054818** *** (0.007300) [7.510]	**0.010423** (0.014008) [0.744]	**0.072659** *** (0.007152) [10.160]	**0.069738** *** (0.008142) [8.566]	**0.076307*** (0.007331) [10.409]	**0.067447** *** 0.006947 [9.709]
Sweden	**-0.053834** *** (0.007357) [-7.317]	**-0.038347** *** (0.007966) [-4.814]	**-0.046943** *** (0.007479) [-6.277]	**-0.059517** *** (0.010604) [-5.613]	**-0.054359*** (0.007366) [-7.380]	**-0.023625** * (0.011753) [-2.010]
Slovenia	**0.032227** *** (0.008710) [3.700]	**0.022138** * (0.009748) [2.271]	**0.048531** *** (0.008215) [5.908]	**0.048557** *** (0.008587) [5.655]	**0.050771** *** (0.008258) [6.148]	**0.049561** *** (0.008266) [5.996]

Note: Robust standard errors in (parentheses) and t-statistics in [square brackets]. Data are from Rounds 3, 6, and 7 of the European Social Survey and the OECD SOCX database. Belgium is treated as the constant in the fixed effect regressions.
*** p<0.01, ** p<0.05, * p<0.1

Consider now the focal association results of IV#2: Family P.R.P.. In our previous Sample that contained only parents, we found that Family P.R.P. spending did not have a statistically significant relationship to depressive symptom score in the population. Strikingly, in our Age 65+ sample, Family P.R.P. expenditure has a coefficient of (-0.009803***). While the coefficient is very very small, predicting only a tiny drop in CES-D 8 score for a unit increase in Family P.R.P. expenditure, it is now a negative and statistically significant coefficient. Thus, IV#2: Family P.R.P. increases in spending have a small, yet significant, inverse relationship to the depression score of those aged 65+.

Turning to IV#3: O.A. + I.R.P., we get the focal coefficient for the main variable we are interested in within this study for this sample. The coefficient for IV#3 is (-0.055413***), again negative, significant with a p-value < 0.01, and this time the second largest negative coefficient we have found among our fixed effect regressions. Thus, in line with our hypotheses, IV#3: O.A. + I.R.P. spending is inversely related to the depressive symptoms of Sample #2's over 65+ population. Furthermore, also aligning with previous hypotheses, this inverse within-country association is higher for this specific population (Sample #2) than both Sample #1: Parents, and as we will see in the next section Sample #3: Total Sample, even as both Sample #1 and Sample #2 still show negative and statistically significant inverse associations between within-country IV#3 spending increases and sample population depressive symptoms.

Looking deeper into specific parts of IV#3: O.A. + I.R.P., there are the disaggregated IV's # 4, 5, and 6. These three independent variables all together make up IV#3: O.A. + I.R.P. IV#4 is

Incapacity Related Programs, and the fixed effects model shows a focal association expenditure level coefficient of (0.014551), a positive and statistically insignificant relationship. IV#5: Old-Age programs fixed effects result in a coefficient of (-0.052014***), negative and statistically significant. IV#6: Survivors expenditure similarly results in a negative and statistically significant coefficient, (0.018870**), which is, however, much smaller than IV#5. Thus, within-country effects of expenditure changes for old-age and survivors social policy expenditure show an inverse relationship with depressive symptoms for Sample #2: Age 65+, results that are in line with our hypotheses. We discuss why IV#4: Incapacity Related Programs did not have a negative and statistically significant coefficient resulting from the fixed effects regression in the next chapter.

4.2.3 Round Three: Sample #3: Total Sample

Finally, we can consider the three fixed effects regressions we have run for Sample #3: Total Sample (N = 91859). For this sample, we have only run the aggregate policy expenditure group independent variables (IV#1, 2, & 3). First, we can examine IV#1 on Sample #3, Total S.P.E. on Total Sample depressive symptom scores. The fixed effects focal association coefficient is (-0.024176**), negative, and statistically significant. Notice, however, that the effect of IV#1 on Sample #3 is far smaller than the association between IV#1 on the depressive symptom score of Sample #2's population (-0.076562***). This could be due to the variance mean in depressive symptom scores in Sample #3 being smaller (see Graph 1), even as it is decreasing, which could lead the fixed effects regression to underestimate the effect (Huntington-Klein, 2021). Shifting to IV#2: Family P.R.P., one sees that this coefficient (-0.007835***) is negative, extremely small, but statistically significant. Therefore, unlike the within-country association examined between IV#2 and Sample #1, these results point to within-country Family P.R.P. spending levels having a very small and significant inverse relationship with depressive symptom outcomes amongst the total sample, unlike in the parents' sample.

Table 10 - Sample #3 Within-Country Fixed Effects of Social Policy Pooled Expenditure on Depressive Symptoms (N = 91859)

	IV#1: Total S.P.E.	IV#2: Family P.R.P.	IV#3: O.A. + I.R.P.
Focal Association: Expenditure Level	**-0.024176 **** (0.007424) [-3.257]	**-0.007835 ***** (0.005371) [-2.571]	**-0.017404 **** (0.006512) [-2.672]
Fixed Components			
Intercept	**2.805037 ***** (0.024561) [114.207]	**2.735366 ***** (0.007141) [388.070]	**2.769303 ***** (0.016587) [166.954]
Country Coefficients			
Switzerland	**-0.034143 *****	**-0.026456 *****	**-0.025884 *****

	(0.005382) [-6.344]	(0.005292) [-5.000]	(0.003922) [-6.600]
Germany	**-0.031866 ***** (0.002972) [-10.721]	**-0.032978 ***** (0.003576) [-9.221]	**-0.030060 ***** (0.002912) [-10.322]
Denmark	**-0.044884 ***** (0.003405) [-13.182]	**-0.043428 ***** (0.003845) [-11.294]	**-0.043700 ***** (0.003503) [-12.476]
Estonia	**0.012075 *** (0.005419) [2.228]	**0.023265 ***** (0.003813) [6.101]	**0.019084 ***** (0.004188) [4.557]
Spain	**-0.004524** (0.003345) [-1.352]	**-0.009097** (0.006104) [-1.490]	**-0.001076** (0.003212) [-0.335]
Finland	**-0.067365 ***** (0.003150) [-21.389]	**-0.066757 ***** (0.003224) [-20.703]	**-0.064772 ***** (0.003344) [-19.372]
France	**0.013800 ***** (0.003312) [4.167]	**0.011294 ***** (0.003199) [3.530]	**0.014200 ***** (0.003424) [4.147]
United Kingdom	**0.003843** (0.003551) [1.082]	**0.011594 ***** (0.003327) [3.484]	**0.002258** (0.004137) [0.546]
Ireland	**-0.022489 ***** (0.003820) [-5.887]	**-0.014808 ***** (0.003087) [-4.797]	**-0.025712 ***** (0.005017) [-5.125]
Netherlands	**-0.018840 ***** (0.004574) [-4.119]	**-0.014331 **** (0.005236) [-2.737]	**-0.014146 ***** (0.003900) [-3.627]
Norway	**-0.070115 ***** (0.003809) [-18.410]	**-0.063599 ***** (0.003377) [-18.836]	**-0.066107 ***** (0.003424) [-19.306]
Poland	**0.005531** (0.003908) [1.415]	**0.005014** (0.006014) [0.834]	**0.014109 ***** (0.003341) [4.223]
Portugal	**0.040757 ***** (0.003388) [12.031]	**0.036050 ***** (0.006414) [5.621]	**0.046365 ***** (0.003314) [13.991]
Sweden	**-0.053679 ***** (0.003230) [-16.617]	**-0.051196 ***** (0.003504) [-14.610]	**-0.051469 ***** (0.003292) [-15.634]
Slovenia	**-0.013756 ***** (0.003789) [-3.631]	**-0.012868 **** (0.004271) [-3.013]	**-0.008607 *** (0.003549) [-2.425]

Note: Robust standard errors in (parentheses) and t-statistics in [square brackets]. Data are from Rounds 3, 6, and 7 of the European Social Survey and the OECD SOCX database. Belgium is treated as the constant in the fixed effect regressions. *** p<0.01, ** p<0.05, * p<0.1

Finally, let us consider the coefficient of the final fixed effects regression we have run between IV#3: O.A. + I.R.P. spending levels and Sample #3 depressive symptom scores. The coefficient is negative and significant (p-value < 0.05), but compared to other associative values is small at (-0.017404**). This coefficient suggests that O.A. + I.R.P. expenditure levels have an inverse relationship with Sample #3 depressive symptom scores, as the O.A. + I.R.P. expenditure levels rise, depressive symptom scores fall. As with the other significant findings from our fixed effect regressions, the coefficient is again very small.

5. Discussion & Conclusion

In this final chapter I present my results in relation to my research question and my three hypotheses. I further discuss my findings in broader relation to the conclusions of other research on the topic, point out pathways for further research regarding this topic, and summarize relevant conclusions from this work in its entirety.

5.1 Discussion

This study contributes to the growing but underdeveloped research field regarding the association between the level of social protection expenditure at the state level and individual mental health outcomes (Niedzwiedz et al., 2016; Parbst & Wheaton, 2023). Through previous research on the economic determinants of mental health, we adopted a determinant perspective to mental health outcomes and followed this idea through a social expenditure framework. Our choice of ESS data was motivated by the reality that there is no other cross-sectional time series data as broad as the ESS that surveys for depression through any form of a standardized and generalizable survey tool. Through the methodological choice of fixed effects regressions, this study explored associations between the sample populations' depressive symptom scores and specific social protection expenditure groups.

This work concerned itself with the research question: *What effects does the expenditure level of European government social policy programs have on an individual's depressive symptom outcomes within those countries?*

According to the fixed effects regression results, the answer to our RQ is that the expenditure level of European government social policy programs has a mild, but still present, **mitigating** effect on individual depressive symptom outcomes within the countries we have observed. This is because the majority of the results in this study estimate small **inverse** relationships between almost every independent variable and the sample's depressive symptom scores. There are some large trends amongst our results that let us claim this answer. Crucially, an overwhelming amount (11 out of 14) of the fixed effect focal association coefficients estimate a negative and significant relationship between our independent variables and our dependent variable across samples. Specifically, the coefficients found can be interpreted to confirm two of the three hypotheses (H1, H2, and H3) that we had for this study. The results slightly contradict the first main claim of H1, but confirm the second claim.

Let's turn to discuss the results in terms of theory and our expected hypotheses. First, H1, which was the hypothesis that we created for the effect we thought increased social expenditure on family policy-related programs may have on parents specifically.

H1: *Increases in European government social expenditure on all **family policy-related programs** have an **inverse** relationship with the population of parents' depressive symptoms.*

Furthermore, we believe that increases in government spending on family policy-related programs will have a small but significant inverse relationship with depressive symptoms in a larger sample population of individuals.

The main result of concern for this hypothesis was IV#2: Family P.R.P & Sample #1: Prents fixed effects focal association coefficient, which *was* negative but was statistically insignificant. However, IV#7 and IV#8 (Family Cash and Family In-Kind Benefits) did show negative and statistically significant effects, and these independent variables together make up IV#2: Family P.R.P. expenditure. Thus, my conclusion is that the statistical insignificance of the IV#2/Sample #1 relationship result is likely a methodological issue resulting from simple fixed effects models underestimating within-unit effects that have low variance over time in the independent variable, which Family P.R.P. did have (refer to Table X to see % of GDP expenditure mean values, Family P.R.P. expenditure variance is very low or nonexistent between years) (Arnold, 2020; Huntington-Klein, 2021). This is a known issue with FE regression models, as they tend to overestimate and underestimate associations when some units observed have very large or very low levels of variation, an issue that is especially relevant when looking at state-level expenditure level change over time (Huntington-Klein, 2021). The inverse relationships between Family P.R.P. spending and other populations were shown by IV#2/Sample#2 and IV#2/Sample#3 having negative and significant FE coefficients. Effects were very small compared to any other independent variable expenditure group, a consequence likely caused by the fixed effects model employed underestimating within-unit effects that have low variance.

H2: *Increases in European government social expenditure on* ***old-age + incapacity-related programs*** *have an* ***inverse*** *relationship with the level of depressive symptoms in the older population (individuals 65+). We also believe that increases in spending on old-age + incapacity-related programs will have a smaller but still significant inverse relationship with depressive symptoms across a larger sample of individuals who are not over age 65.*

Turning to a discussion on H2 results, we found that increases in IV#3: O.A. + I.R.P. expenditure did have an inverse relationship with depressive symptoms across both the older population sample (S#2) and the same inverse relationship was exhibited in both S#1 and S#2, although they had smaller estimations of effect. The results confirm all parts of H2. Furthermore, the results showed increases in IV#3 expenditure had nearly as large a within-unit effect on depressive symptoms as the total social expenditure (IV#1), which suggests that O.A. + I.R.P. expenditure has an outsized effect on depressive symptoms, something that other researchers have hypothesized about social protection expenditure's mental health effects on specific populations (O'Campo et al., 2015; Niedzwiedz et al., 2016). When we looked at the within-IV#3 group policies, which were IV's #4-6, we found that IV#4 and IV#6, I.R.P. and Survivors Benefits respectively, either did not have significant associations with depressive symptom outcomes or had positive effects. I believe this to be a methodological issue, with fixed effects regressions overestimating or underestimating certain countries in the association and thus skewing the association (the same issue encountered with IV#2 and Sample #1). Again, IV#4 and IV#6 both have very low variances in expenditure levels over the three years of data we sampled. This could be fixed by the addition of more years of data if more data on depressive symptoms with a reliable sample size could be found.

Finally, we confirmed our H3 hypothesis through results that showed IV#1: Total Social Expenditure to have a significant inverse relationship with depressive symptom outcomes across all of our samples.

H3: *Increases in European government* ***total social expenditure*** *have an* ***inverse*** *relationship with the whole country's population's depressive symptoms. We expect this inverse relationship between total social expenditure and depressive symptoms to hold across specific populations such as parents and those over age 65+.*

Unsurprisingly, IV#1 had the largest coefficients and the greatest effects, something we did not hypothesize, but a finding that is in line with previous research on other types of relationships between total groupings of social protection expenditure and depressive symptoms (Levecque et al., 2011; Niedzwiedz et al., 2016).

As previously discussed, this study is not without limitations, and my limitations suggest there are many pathways for further research on this particular topic. Particularly, implementing hierarchical multilevel fixed and random effects models could have resulted in more depth for this research, exploring individual controls and between-country interaction effects (Giesselmann and Schmidt-Catran, 2019). Additional individual controls would have enabled analysis of effects on a greater number of populations. Other statistical tools and techniques could be applied to analyze the data more closely and help broaden the interpretation of the data. Between-effects would add a whole new component to this research. A broadening of the samples or a deepening of the samples would add considerably to investigating the potential within-country effects of social protection expenditure on depressive symptoms. The same holds true for adding in more disaggregated public social protection expenditure data, ie. looking directly at specific policies instead of aggregates.

This study's analysis contributes theoretically to the field of socioeconomic determinant theories of mental health by showing that there are small inverse associations between in-country social protection spending levels and individual depressive symptoms. Our findings suggest that social policy spending levels *do* have an impact on the mental health of the individuals it affects. These findings signify that changes in social protection program spending levels do matter, albeit perhaps not at an entirely massive level. This provides an addition to the analysis of other research looking at depression and general socioeconomic status, which has found that within-country spending on a range of social protection programs is not as relevant for depressive symptom mitigation as the simple historical presence of social protection programs at all (Parbst & Wheaton, 2023, p. 15). Our findings contradict part of Parbst & Wheaton's research, in the sense that we do find minor moderating effects of changes in social protection expenditure levels within country contexts. However, we concur with their conclusions that within-country expenditure level effects are not as pronounced as between-country differences in welfare system spending. For example, looking at Parbst & Wheaton's (2023) recent research, between-country differences seem to provide large associations with depressive symptom outcomes. This study's findings are important in that they show a significant within-country effect of expenditure level change on depressive symptom outcomes, however, it is not a large effect. Instead, my findings suggest that social protection policies mostly affect individual depressive symptoms and mental health as a "package", and further that there may be effective 'cutoffs' to the depressive symptom mitigation effects of social protection spending. In this sense, perhaps individual program spending has a 'diminishing return' in terms of its depressive symptom reduction effects after certain levels of spending/levels of institutional creation. This idea tracks with some research on maternity leave policies and depression amongst women, as while more generous leave policies did positively impact the mental health of new mothers, the biggest impacts were between those with no maternity leave policy, and those with any maternity leave policy (Avendano et al., 2015). Perhaps similarly, it is the presence of a social safety net that provides the major modification to the overall level of individual depressive symptoms across a population, even as within-country spending levels do play a part in affecting individuals' depressive symptoms, however small.

5.2 Conclusion

To summarize, this study centered around the question: *What effects does the expenditure level of European government social policy programs have on an individual's depressive symptom outcomes within those countries?* My results contend that the expenditure level of European government social policy programs has a mild, but still present, mitigating effect on individual depressive symptom outcomes within the countries we have observed. This is because the majority of the results in this study estimate small inverse relationships between almost every independent variable and the sample's depressive symptom scores.

The key findings of this study are that increases in spending for *every* major group of social protection policy expenditure we examined (IV's #1-3) had an inverse relationship with depressive symptom scores across all three of our samples, except for in the case of IV#2: Family P.R.P. spending and Sample #1: Parents Sample. However, our findings suggest associative inverse effects between social protection policy expenditure and depressive symptoms within countries are mild at best, and miniscule for the majority of associations.

According to my results, all increases in expenditure levels examined for Sample #2: Age 65+ had the largest inverse associations with depressive symptoms in that sample population. Furthermore, IV#1: Total Social Protection Expenditure had the largest effects across two of the populations, Sample #2: Age 65+ and Sample #3: Total Sample, as well as the largest effect overall throughout all of the FE regressions run (-0.076562***) for IV#1 and Sample #2: Age 65+. A slim minority of independent variables had positive or statistically insignificant associations with depressive symptoms (3 coefficients out of 14). This was likely due to our model skewing results towards parts of the data with more variance, as two of these independent variables (IV#4: I.R.P. & IV#6: Survivors) had very low expenditure effectively no variance over our three years of country data for the variable.

Major trends identified in the results confirmed all parts of two hypotheses posed in this study (H2, and H3), and only contradict the first claim of H1. Specifically, results found that while family policy-related program expenditure had a significant and inverse relationship to depressive symptom scores in our total and age 65+ populations, it did not have a significant inverse relationship in our parents' sample. Thus the first part of H1 is null, while we did confirm the second part of the hypothesis.

Taking a more focused approach on only within-country effects and disaggregating the social protection expenditure data for interaction and analysis, this study has been a sort of pilot approach to this specific topic. This is mainly due to previous research on the topic not looking at within-effects and also not controlling for major confounding variables such as country GDP (Niedzwiedz et al., 2016). While other scholars such as Parbst & Wheaton (2023) have looked at within-country effects of social protection expenditure on depression with ESS data, they sought to answer different questions, and thus their grouping of all the social protection expenditure data left what I understood to be a large gap in the literature on this topic.

Because of the mostly uncharted nature of this study, it would have benefitted from a deeper analysis of more expenditure variables, as many as possible ideally, and I believe would have produced a greater depth of results and interesting interactions if a more complex methodological choice (discussed previously) could have been made. Individual-specific controls are one tool that would have added a large amount of depth and specificity that I believe this study lacks. Nevertheless, I faced issues in terms of time and familiarity when making choices regarding how this study would be conducted. Although this research has pronounced limitations, this study provides a foundation for further research into the within-country effects of social protection expenditure levels and depression. Ideally, it can spur investigation of the topic with more rigorous methods, different data, and greater levels of specificity in terms of individual policy programs' effects or in other ways.

I hope this research can contribute evidence that there are policy actions and new solutions to economic determinants of mental health outcomes in OECD nations.

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Appendix

Additional data, tables, and graphics that weren't necessarily essential or helpful to include in the paper's main body are included in this section.

Appendix A

Appendix X - Disaggregated Within Country Means of Depression by Sample Type

	Sample #1: Parents	***Sample #2: Age 65+***	***Sample #3: Total***
	Depression (Mean)	**Depression (Mean)**	**Depression (Mean)**
Country	**Range: 8-32**	**Range: 8-32**	**Range: 8-32**
Belgium	15.69	15.76	15.47
Denmark	14.87	14.97	14.77
Switzerland	15.20	15.26	15.12
Germany	15.10	15.18	15.01
Estonia	16.32	16.70	15.95
Spain	16.12	16.27	15.52
Finland	14.61	14.83	14.43
France	15.82	15.94	15.66
United Kingdom	15.81	15.82	15.63
Ireland	15.40	15.58	15.26
Netherlands	15.45	15.53	15.33
Norway	14.48	14.59	14.47
Poland	16.93	17.69	15.79
Portugal	16.71	16.92	16.26
Sweden	14.75	14.97	14.67
Slovenia	15.84	16.59	15.36
Total Mean Score	**15.53**	**15.78**	**15.30**

Appendix B

Table X - Within Country Descriptives of Depression by ESS Round

	ESS Round 3 (2006)			ESS Round 6 (2012)			ESS Round 7 (2014)		
	Depression (Mean)			Depression (Mean)			Depression (Mean)		
Country	**Parent**	**Age 65+**	**Total**	**Parent**	**Age 65+**	**Total**	**Parent**	**Age 65+**	**Total**
Belgium	15.71	15.69	15.38	15.81	16.06	15.44	15.52	15.52	15.59
Denmark	15.03	15.25	14.81	14.82	14.98	14.74	14.75	14.70	14.77
Switzerland	15.23	15.60	15.12	15.43	15.34	15.24	14.93	14.75	15.01
Germany	15.15	15.65	15.03	15.22	15.12	15.14	14.93	14.82	14.86
Estonia	16.70	17.17	16.26	16.39	16.70	15.92	16.02	16.37	15.77
Spain	16.06	16.29	15.34	16.02	16.21	15.48	16.25	16.32	15.72
Finland	14.49	14.73	14.35	14.74	14.99	14.47	14.58	14.76	14.46
France	15.64	15.78	15.55	16.07	16.18	15.81	15.69	15.81	15.63
United Kingdom	15.87	16.05	15.68	15.87	15.91	15.65	15.70	15.53	15.54
Ireland	15.63	15.87	15.49	15.32	15.41	15.15	15.38	15.53	15.20
Netherlands	15.42	15.73	15.28	15.43	15.50	15.39	15.50	15.41	15.30
Norway	14.37	14.67	14.39	14.53	14.60	14.48	14.55	14.52	14.54
Poland	16.95	17.80	15.76	16.84	17.63	15.74	17.01	17.68	15.89
Portugal	17.00	17.31	16.57	16.26	16.44	15.80	16.88	17.08	16.48
Sweden	14.70	15.08	14.53	14.72	14.79	14.65	14.84	15.06	14.83
Slovenia	16.40	17.11	15.67	15.60	16.53	15.19	15.64	16.13	15.17
Total	**15.65**	**15.99**	**15.33**	**15.57**	**15.77**	**15.29**	**15.51**	**15.63**	**15.27**