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Introduction and Extended Abstract

This thesis is composed of three empirical studies, united by the premise that non-material dimensions – such as social capital, subjective happiness, and the environment – play a crucial role in influencing well-being, public health, and social cohesion. By focusing on different contexts (Brazil, the United States, and Latin America and the Caribbean) and distinct outcomes (mental health, substance use, and institutional trust), the three studies jointly investigate how social and ecological factors interact with individual vulnerabilities and societal stability. Together, they contribute to a broader, human-centered understanding of well-being that goes beyond material conditions and economic indicators, emphasizing the importance of social, psychological, and environmental determinants in shaping both individual and collective outcomes.

The first paper, entitled **"The therapeutic power of social capital: a quantitative study on happiness and mental health in peripheral Brazil"**, investigates the protective and therapeutic role of social capital in shaping well-being among individuals with psychiatric disorders, mild psychological conditions, and a control group without diagnoses. Fieldwork was carried out in a peripheral neighborhood in Fortaleza, Ceará, producing 504 structured interviews on socioeconomic indicators, social capital, mental health status, and quality of life. Using nonparametric balancing techniques (PSM and npCBGPS) combined with OLS and Ordered Probit models, the analysis shows a positive association between social capital and subjective happiness across all groups, with bootstrapped confidence intervals confirming the robustness of the results. Nonlinearity tests indicate that individuals with moderate to severe conditions benefit most, although marginal gains diminish beyond a certain threshold. Overall, the study emphasizes the therapeutic role of social capital in preserving subjective well-being – especially among individuals with mild mental health vulnerabilities – and calls for targeted public health interventions in socially marginalized neighborhoods of Fortaleza.

The second paper, entitled **"Can subjective happiness protect against crack/cocaine use and injection drug use? An instrumental variable study of the U.S. population"**, examines the causal relationship between happiness and severe forms of substance use. Addressing the problem of reverse causality, the paper specifically seeks to shed light on the directionality of the effect of happiness in its relationship with crack/cocaine use and drug injection. Drawing on nationally representative data from the U.S. General Social Survey and employing an instrumental variable approach (2SRI), results show that higher levels of happiness significantly reduce the likelihood of crack/cocaine use and drug injection, even after controlling for demographics, socioeconomic conditions, and adverse adolescent events. Exploratory analyses further indicate that individuals raised in large towns or suburbs at age 16 are more likely to use crack/cocaine, whereas living with both parents reduces risk; higher family income at age 16, however, is positively associated with substance use. These findings clarify the direction of the relationship, implying that happiness serves as a buffering factor against substance use and subsequent addiction. Policy implications stress the importance of prioritizing well-being, social capital, and collective resilience over punitive and prohibitionist approaches and individual responsibility frameworks.

The third paper, entitled "**Does forest cover loss undermine institutional trust? A cross-country analysis from Latin America and the Caribbean (2008–2023)"**, studies the impact of forest degradation on citizens' trust in public institutions. A composite measure of institutional trust was constructed from items assessing confidence in the president, congress, political parties, elections, municipality, police, and the army. Combining AmericasBarometer survey data with geospatial tree cover loss metrics from Global Forest Watch produced a macro-panel dataset of nearly 200,000 observations from LAC countries (2008–2023) with high spatial and temporal granularity. To address potential reverse causality, lagged fixed effects models were estimated using two indicators: *general tree cover loss* (≥10% initial canopy cover) and *specific tree cover loss* (≥50% and ≥70%) in critical biomes. Both measures show a significant negative association with institutional trust. Disaggregated analyses reveal particularly marked effects for trust in the army**,** congress, elections, and political parties. Moreover, short-term within-country and long-term structural forest loss across countries are linked with declining institutional trust. Forest cover loss constitutes an ecological crisis and a critical threat to the legitimacy of public institutions in Latin America and the Caribbean.

Overall, these three studies demonstrate that subjective well-being, social capital, and environmental stability are interdependent drivers of both individual and collective outcomes. They suggest the need for integrated approaches in public health, social policy, and environmental governance to build more resilient, inclusive, and trustworthy societies.

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“No one educates anyone else, no one educates themselves, people educate each other, mediated by the world.” — Paulo Freire, *Pedagogy of the Oppressed*, 1968

“Ninguém educa ninguém, ninguém educa a si mesmo, os homens se educam entre si, mediatizados pelo mundo.” — Paulo Freire, *Pedagogia do Oprimido*, 1968

“Nessuno educa nessuno, nessuno si educa da solo; gli uomini si educano insieme, attraverso il mondo.” — Paulo Freire, *La Pedagogia degli Oppressi*, 1968

"Nihče ne izobražuje nikogar drugega, nihče se ne izobražuje sam; ljudje se izobražujejo drug z drugim, posredovani skozi svet." — Paulo Freire, *Pedagogika zatiranih*, 1968

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Chapter 1

1. The therapeutic power of social capital: a quantitative study on happiness and mental health in peripheral Brazil

Abstract

This study explores the relationship between social capital and subjective happiness among individuals with mental health conditions. It investigates the protective and therapeutic role of social capital in shaping well-being across three groups: individuals with mild psychological conditions (MSM), those with diagnosed psychiatric disorders (CAPS), and a control group without mental health diagnoses (SEM). Fieldwork in a peripheral neighborhood of Fortaleza, Ceará, Brazil, produced 504 structured interviews covering socioeconomic indicators, social capital dimensions, mental health status, and quality of life. Respondents were mostly women with low levels of education who identified as Black, light-skinned Black, or Indigenous. OLS and Ordered Probit regressions reveal a strong positive association between social capital and subjective happiness, particularly in MSM and CAPS groups. Robustness checks using alternative specifications and balancing techniques confirm the consistency of the results. Moreover, nonlinearity analyses indicate that individuals with severe conditions require higher levels of social capital to experience peak happiness, while those with mild symptoms benefit more rapidly but reach saturation earlier. These findings emphasize the critical role of social capital in enhancing well-being among vulnerable populations and support the need for targeted public health interventions in marginalized urban areas such as the peripheries of Fortaleza.

1.1 Introduction

Individuals living with mental health conditions often face elevated vulnerability in their daily lives, particularly in developing regions. Mental health is not merely a personal issue but a significant public health concern, increasingly recognized as a priority for prevention, treatment, and social protection (Patel *et al.*, 2018; WHO, 2022a). As emphasized by the World Health Organization (WHO, 2021; 2022b), mental health is a fundamental component of subjective well-being, influencing individual behavior, decision-making, and overall life outcomes. It also underpins key aspects of human development, such as identity formation, social relationships, and civic participation.

According to Ferrari (2022), the age-standardized disability-adjusted life years (DALYs) for mental disorders remained relatively stable between 1990 and 2019. However, the total number of DALYs increased by 55.1%, a trend that places growing pressure on health systems, especially in low- and middle-income countries, where service coverage remains limited and barriers to care persist. In these contexts, the burden of mental health is exacerbated by structural adversity, conflict, interpersonal violence, and poverty, while access to care remains inadequate. Although effective interventions exist and have demonstrated the potential to reduce symptom severity and mortality risk, their implementation is frequently constrained by underfunding, stigma, and limited health infrastructure. Even in high-income countries, treatment often fails to reach those most vulnerable populations. This underscores the need to expand and improve access to mental health services, particularly in regions marked by social exclusion and fragile public systems.

This study investigates the role of social capital as a determinant of subjective happiness among individuals living with mental health conditions. Specifically, it explores whether social capital can act as a protective and therapeutic factor, potentially mitigating the negative effects of mental health severity on subjective happiness and well-being. Social capital is conceptualized here as a multidimensional construct that includes friendships, frequency of social interactions, social participation, social inclusion, and volunteering. Subjective happiness, in turn, refers to individuals' perceptions of overall life satisfaction and emotional well-being over time.

The research was conducted in peripheral neighborhoods of Fortaleza, Brazil, through standardized interviews with individuals experiencing different levels of mental health vulnerability. Three population groups were identified: individuals with mild psychological distress, individuals with psychiatric diagnoses, and a control group with no reported mental health conditions.

Brazil represents a high-risk context for mental health issues, recording a high prevalence and burden of mental health disorders. While mental health has been recognized as a constitutional right since 1992, following the implementation of Brazilian Psychiatric Reform (*Reforma Psiquiátrica Brasileira*), significant challenges persist. In vulnerable urban contexts, residents frequently face structural adversities in social and health inclusion, including financial instability, inequality, environmental deprivation, limited access to basic services, and exposure to violence (IPEA, 2021).

These perspectives frame mental health as a socially embedded experience, shaped by personal, relational, and structural factors. Understanding how social resources like social capital operate in vulnerable contexts is essential in addressing mental health inequality. The link between mental health, subjective happiness, and social capital forms the conceptual basis of this study, offering insight into how interpersonal and structural supports influence well-being among individuals experiencing mental health conditions.

Following this line, this study carries several potential policy implications. In particular, it may inform the design of public health interventions that integrate mental health support with community-based resources. Recommended actions include reinforcing relational networks among peers and community members, promoting social inclusion to combat stigma, and encouraging participation in collective activities to reduce passivity and social isolation. Furthermore, the findings may support the development of collaborative initiatives involving local public mental health services, NGOs, civil society actors, and grassroots organizations, in order to deliver more integrated and accessible interventions based on social relationships and community engagement.

This chapter is structured as follows. Section 1 and 2 present the theoretical and conceptual framework underpinning the study, including definitions and key literature on mental health, subjective happiness, and social capital. Section 3 introduces the contextual framework. Section 4 sets the research question and the rationale behind the hypotheses. Section 5 describes the dataset and variables used, followed by Section 6, which presents descriptive statistics. Section 7 and 8 detail the empirical strategy, including model specification and balancing techniques. Section 9 reports the main results, while Section 10 focuses on robustness checks and nonlinearity tests. Finally, Section 11 provides a discussion of the findings, followed by a concluding section.

The analysis was conducted using RStudio.

1.2 Theoretical framework

Before studying the relationship between social capital, mental health, and subjective happiness, this section develops an integrated theoretical framework for these concepts, aiming to understand how non-material dimensions of social life contribute to subjective well-being according to existing theories and foundational streams of thought. It is divided into three parts. First, it explores the conceptualization of mental health as a multidimensional and socially embedded condition. Second, it outlines major theories of subjective happiness, emphasizing the distinction between material and non-material drivers of well-being. Third, it examines social capital as a structural and relational resource that shapes both individual mental health and life satisfaction.

1.2.1 Mental health

Mental health is not merely the absence of illness, but a dynamic state deeply interwoven with overall quality of life. As Manwell *et al.* (2015) argue, mental health results from the interaction of biological, psychological, and social factors that enable individuals to manage stress, build resilience, and maintain adaptability. Their transdomain model highlights the interconnection between physical, mental, and social well-being, suggesting that promoting mental health empowers individuals to gain competence, control, and purpose in their lives.

Building on this perspective, studies such as Connel *et al.* (2014) identify key domains that shape the lived experience of individuals with mental health conditions: well-being and ill-being, relationships and belonging, self-perception, autonomy, activity, hope and hopelessness, and physical health. Fusar-Poli *et al.* (2020) further emphasize the importance of social connections – particularly family and significant others – life purpose, and quality of life, not only as coping resources but also as protective factors that support recovery and long-term mental wellness. Alongside these experiential dimensions, mental health vulnerability is also influenced by ascribed characteristics (e.g., gender, ethnicity, genetic predisposition) and acquired conditions developed throughout life, such as employment, social networks, or health behaviors (Ng *et al.*, 2014; Delgadillo, 2018). These factors intersect with social structures, potentially worsening pre-existing conditions or increasing susceptibility to new disorders (WHO, 2022b).

Beyond individual and experiential dimensions, scholars have increasingly emphasized the role of social determinants of mental health, which can be categorized into *upstream* and *downstream* factors. Upstream factors refer to broader structural conditions (economic opportunities, governance, and public policies) that shape the society in which individuals live. Downstream determinants include more immediate influences such as neighborhood quality, education, family dynamics, occupational status, risk behaviors, and access to care (Leighton & Dogra, 2009; Alegría *et al.*, 2018; Palmer *et al.*, 2019). These layers often interact with upstream factors and may also act through downstream determinants in affecting day-to-day life and, ultimately, individual mental health.

To interpret these patterns, two theoretical frameworks have been widely applied to explain the interplay between mental health and social context. The *social causation hypothesis* posits that mental health can be negatively affected by socioeconomic disadvantages, such as deprivation, social exclusion, and low educational attainment. In contrast, the *selection-drift hypothesis* implies that mental health disorders precede and contribute to downward social mobility, increasing the risk of unemployment, housing insecurity, school dropout, and social stigma (Dohrenwend *et al.*, 1992;

Finegan *et al.*, 2017). Both mechanisms imply a social gradient, as individuals positioned lower on the socioeconomic spectrum tend to report worse mental health outcomes, highlighting that mental health cannot be fully understood without considering broader societal influences and subjective well-being.

1.2.2 Subjective happiness

The concept of subjective happiness has been extensively explored across psychology, sociology, and economics. Following World War II, per capita Gross National Product (GNP) became a dominant metric to evaluate not only economic development but also individual well-being and life satisfaction. As GNP increases, so does individuals' standard of living, which in turn enhances social status and purchasing power relative to those with lower incomes.

A key contribution to this debate is the *Easterlin Paradox* (Easterlin, 1974), which supports the view that happiness is often shaped by social comparison: individuals assess their well-being relative to culturally embedded reference groups. Consequently, people with lower incomes typically report lower happiness levels compared to those at the top of the income distribution. Although rising income can initially increase happiness, this effect tends to level off over time. As societal income grows, so do the expectations and reference standards, diminishing the long-term impact of personal income growth on happiness (Easterlin, 2003; Easterlin & O'Connor, 2020). Easterlin's *Setpoint Theory* further argues that subjective happiness is largely influenced by stable factors such as personality traits and genetic predisposition. Life events – such as marriage, unemployment, or illness – may cause short-term fluctuations, but most individuals tend to return to their baseline happiness level over time (Easterlin & Switek, 2014; Anusic *et al.*, 2014; Ormel *et al.*, 2017).

Building on these economic debates, psychological perspectives have broadened the definition of happiness as a multidimensional experience. Cheng & Furnham (2000) and Hills & Argyle (2002) identified three main components shaping happiness: life satisfaction over time, frequency of positive emotions, and the relative absence of negative feelings. Similarly, Lyubomirsky (2007) describes happiness as a combination of joy, psychological well-being, and a sense of meaning in life. In contrast to the hedonic view of happiness – which emphasizes pleasure and the avoidance of pain – the *eudaimonic* perspective focuses on living a meaningful, virtuous life based on the fulfillment of psychological needs. Rooted in Aristotelian thought, this approach is supported by Ryan *et al.* (2008) and Frey (2018), who, drawing on Self-Determination Theory, argue that autonomy, competence, and interpersonal ties are essential to long-term happiness and human flourishing. In this view, subjective happiness appears as the inner satisfaction derived from pursuing and achieving personally significant goals, in line with the Aristotelian notion of *eudaimonia* (Crespo & Mesurado, 2015). Therefore, relying on material consumption alone to evaluate happiness provides an incomplete picture. While income is positively associated with happiness, its impact diminishes over time. Non-material dimensions – such as genetics, personality, social capital, environmental conditions, and cultural context – play crucial roles in shaping happiness (Frey, 2018; Easterlin & O'Connor, 2022; Bartolini *et al.*, 2023).

This multidimensional view is further reinforced by Bartolini (2011), who argues that materialistic societies driven by extrinsic motives like wealth and status erode genuine happiness by weakening social bonds and prosocial behavior. Materialism is associated with lower empathy, generosity, cooperation, and authenticity, and with higher levels of stress, anxiety, and emotional distress. By contrast, individuals who prioritize intrinsic values – such as friendship, solidarity, and civic responsibility – report greater self-esteem, self-realization, and overall psychological well-being. Within this framework, one of the most influential non-material drivers of subjective happiness is social capital.

1.2.3 Social capital

Social capital is a multifaceted and foundational concept, crucial for understanding collective well-being and democratic cohesion. Putnam (1994; 1995) defines social capital as the synergy of social networks, shared norms, and interpersonal trust that enable coordinated collective actions for mutual benefit. When these elements create bridging ties across diverse social groups, social capital becomes a unifying force that promotes inclusive cooperation and benefits the wider community. A key component of social capital is *c*ivic engagement, understood as individuals' participation in community life beyond formal political participation, rooted in a sense of collective responsibility. This is closely linked to social trust (trust in others), which, although distinct from political trust (trust in institutions), is often empirically related. Social capital theory reveals a reciprocal dynamic where interpersonal ties build trust, which in turn enhances individuals' capacity for cooperation and participation.

Building on Putnam's conceptualization, Fukuyama (2002) expands this framework by presenting social capital as a multidimensional construct rooted in real social relationships, where shared norms and values guide behaviors and enable individuals to pursue common interests, essential for democratic vitality. From this perspective, social capital has cultural and utilitarian functions, enhancing returns on physical and human capital and promoting economic productivity and social cohesion. Fukuyama also argues that social capital is not a pure public good, but a private good with potential positive and negative externalities. While networks such as families, associations, or online communities can foster trust, reciprocity, and honesty – generating broad social benefit – certain forms of social capital may reinforce exclusion, in-group bias, or harmful behaviors. Like other forms of capital, social capital has a dual nature, thus it is important to evaluate not only its presence within a society, but also its orientation, considering bridging dynamics and bonding patterns with potentially adverse social consequences.

To further refine the analysis, Claridge (2018) distinguishes between *internal* and *external* ties, each with individual and collective components. *Internal ties* include individual social capital, which derives from personal relationships used for individual benefit, and collective social capital, available within the internal structure of a group or organization and used by the collective. *External ties* refer to social relationships that cross boundaries: individual external ties provide access to outside networks that benefit both the person and the group, while collective external ties connect collectives to other groups, generating broader social resources and potential benefits.

Taken together, these perspectives highlight that social capital is not only a structural resource but also a determinant of individual well-being (Bartolini *et al.*, 2007; Easterlin & O'Connor, 2022; Pancheva & Vásquez, 2022). Unlike material consumption – which offers only a partial view of well-being – non-material factors, particularly social capital, play a central role in shaping subjective happiness. Following this perspective, Bartolini (2011) conceptualizes social capital through elements such as friendships, participation in community life, social identity, support networks, and interpersonal trust. He emphasizes that while societies tend to overinvest in medical treatment, they frequently neglect social relationships, which serve as powerful preventive mechanisms against illness and psychological distress. Even in advanced healthcare systems, the absence of meaningful social ties can significantly undermine overall well-being.

The relevance of social capital becomes even more salient in the field of mental health. Rowling *et al.* (2002) describes mental health not merely as the absence of illness, but as the capacity to engage in reciprocal relationships, cultivate subjective well-being, and pursue both personal and collective goals grounded in fairness and justice. From this perspective, relational connectedness is not only therapeutic but also foundational to resilience and long-term recovery.

1.3 Literature review

The relationship between social capital, mental health, and subjective happiness is complex and requires specific analytical attention. Given the interdisciplinary nature of this study, the literature review is organized into three thematic sections: the impact of social capital on happiness, the reciprocal links between mental health and happiness, and the role of social capital in promoting or undermining mental health. The section synthetizes evidence from economics, psychology, and public health to provide the empirical foundation for the tested hypotheses, with a specific focus on the non-material determinants of well-being.

1.3.1 Social capital and happiness

The literature suggests a complex interplay between income, social capital, and happiness, with growing support for the idea that non-material factors, particularly social capital, may have a lasting and significant impact on life satisfaction. Putnam's research (2001) revealed that happiness increases alongside levels of social capital. The finding revealed that while higher community social capital tends to boost happiness, income does not have the same effect, indicating that the benefits of social capital far exceed those associated with material wealth. This discovery supported the view that the advantages of human and social capital go well beyond merely enhancing material living standards. Following this scenario, Bartolini *et al.* (2007) and Bartolini & Sarracino (2014) emphasized the positive relationship between social capital and happiness, particularly in terms of subjective well-being, over the medium and long term. Their research confronted social capital and GDP, showing that GDP, as an indicator of economic growth, has a more pronounced effect on happiness in the short time while social capital in the medium and long term, confirming the *Easterlin paradox*. Vendrik's (2013) study, using SOEP panel data from 1984–2007, applied an error-correction model to examine short- and long-term effects of current and anticipated future income on life satisfaction. The findings indicated that while current income positively impacts life satisfaction, anticipated future income does not. Over time, people fully adapt to income changes, making long-term income effects negligible. However, social reference income, related to others' income in one's social group, negatively affects long-term satisfaction, explaining the *Easterlin Paradox*. Most adaptation to income and social reference changes occurs within three years, challenging the psychological *Set-Point Theory* by revealing enduring effects of social reference income and other factors. Moreover, Quoidbach *et al.* (2010) experimentally examined how wealth affects the ability to savor positive emotions and everyday experiences. They found that wealthier individuals report lower savoring ability, which undermines their enjoyment of small pleasures, and the emotional benefits often associated with wealth. Their findings support the notion that access to life's luxuries can impair enjoyment of simple pleasures – such as spending less time savoring a piece of chocolate – with mere perception of wealth being sufficient to reduce savoring.

Several studies explored the relationship between happiness and various components of social capital. Bjørnskov (2008) investigated the link between social trust and happiness in the U.S. using panel data from 1983 to 1998. The findings, supported by an instrumental variable approach, reveal a causal relationship in which increases of social trust result in greater happiness. The study highlighted that even small gains in social trust can significantly enhance happiness over time, indicating that these positive effects may emerge gradually. Rodríguez-Pose & von Berlepsch (2014) examined the relationship between subjective happiness and three key dimensions of social capital: social and institutional trust, social interactions, and norms and sanctions. Using European Social Survey data of 2006 and 2008, their findings confirm a strong and positive impact of informal social interaction, interpersonal trustworthiness and trust in the institutional system on subjective happiness, after controlling for individual characteristics and macroeconomic factors. Majeed & Samreen (2020), conducted a cross-country analysis of panel data from 89 countries between 1980 and 2017, finding that all indicators of social capital positively correlate with happiness, with generalized trust and trust in institutions being the most significant predictors. Similarly, Kamarudin *et al.* (2020) found that bonding social capital, bridging social capital, and linking social capital are positively related to happiness in Malaysia. Pancheva & Vásquez (2022), using longitudinal data from the U.S. population, investigated the link between subjective well-being and four dimensions of social capital: personal relationships, social network support, civic engagement, trust with cooperative norms. Their findings consistently supported the positive influence across all four dimensions. Sharma (2023) observed that happiness is strongly influenced by community belonging, trust and confidence aggregates. Additionally, Addae (2020), examined familial social capital in Ghana and found that a sense of belonging, autonomy support, and family control are protective factors for adolescents' life satisfaction and happiness, even amid socioeconomic challenges. Concerning trust in institutions, which represents a factor influencing happiness and well-being, Mochón Morcillo & de Juan Díaz (2016) reported a positive association between institutional trust and happiness in Latin America. Similarly, Bachmann *et al.* (2023) found that higher trust in political institutions enhances life satisfaction, while Crowley & Walsh (2018) emphasized that institutional trust has one of the strongest marginal effects on life satisfaction, underscoring the crucial role of trustworthy institutions in promoting societal well-being.

Conversely, Ram (2010) reevaluated the relationship between social capital and happiness across various cross-country samples, finding a weak connection between the two. Instead, the author identified a strong positive correlation between income and happiness. Using new instrumental variables and controlling for unobserved heterogeneity, Powdthavee (2010) reexamined the role of income in happiness, finding that its impact may be nearly double previous estimates.

1.3.2 Mental health and happiness

Extensive research has explored the bidirectional relationship between mental or general health and happiness. Early studies in the United States used large-scale surveys to examine this link across psychological, epidemiological, and social science fields (Gurin *et al.*, 1960; Bradburn & Caplovitz, 1965; Berkman, 1971). Argyle (1997) argued that happiness positively impacts health, with social relationships, leisure activities, and work accomplishments enhancing happiness and indirectly supporting physical health. Further research supported this link, showing that happier individuals report better self-rated health, fewer chronic conditions, and better physical health over time (Siahpush *et al.*, 2007). Happiness appears to promote health by reducing stress and encouraging healthier behaviors (Sabatini, 2014; Kyriopoulos *et al.*, 2018).

Conversely, good health also fosters happiness, with satisfaction with one's health being closely linked to overall life satisfaction and perceptions of community well-being (Willits & Crider, 1988). Evidence from various regions adds depth to this perspective. For instance, Yiengprugsawan *et al.* (2012) found that in Thai adults, positive and negative mental states are strongly linked to happiness and life satisfaction, while mental capacity and quality had limited effects. Similarly, Senasu *et al.* (2018) showed that mental and moral capacities – referring to decision-making abilities and altruism – play a significant role in shaping happiness through quality-of-life factors. In elderly populations, Mahmoodi *et al.* (2022) called attention to mental health as a key happiness factor, alongside education and healthcare access. Among healthcare workers in China, Feng *et al.* (2022) further demonstrated how high stress levels reduce happiness, underscoring stress as a critical pathway.

Cross-cultural studies also reveal context-specific dynamics. Almadani & Alwesmi (2023) observed an inverse association between happiness and mental health scores among Saudi women, except for social dysfunction, which correlates positively. In Abu Dhabi, Badri *et al.* (2022) documented the complex interplay between happiness, self-rated health, and mental well-being, showing that while mental health and positive emotions align with happiness, depression and calmness exhibit asymmetric associations. Adding a phycological nuance, Blasco-Belled *et al.* (2021) examined the "fear of happiness" phenomenon, finding it positively associates with depression and suggesting that fearing happiness may reinforce negative worldviews.

Beyond mental health perspectives, lifestyle and environment conditions also contribute to happiness outcomes. Physical exercise has consistently been linked to life satisfaction and collective well-being (Gschwandtner *et al.*, 2015; Rasciute & Downward, 2010). By contrast, severe illness and adverse environmental exposures – such as air pollution – can diminish happiness, while public health interventions aimed at improving well-being tend to strengthen community-level happiness (Mohammadi *et al.*, 2022; Zhang *et al.*, 2017; Lee & Yoon, 2020).

1.3.3 Social capital and mental health

Research on the relationship between social capital and mental health often yields complex and varied interpretations. A substantial body of evidence proposes that higher levels of social capital are positively associated with improved mental health outcomes. For instance, increases in both cognitive social capital – which includes factors like trust, mutual support and perceived quality of relationships – (Forsman *et al.*, 2011; Wind *et al.*, 2011) and structural social capital – involving networks, community organizations, and social connections – have been shown to enhance mental health (Hamano *et al.*, 2010). Looking at specific components, Kashcheeva (2019) found that generalized and individual trust significantly reduce mental health disorders among the elderly population in Russia. In a similar vein, Backhaus *et al.* (2020) identified a strong inverse association between social capital – both at the individual and national levels – and depressive symptoms. Students with low perceptions of individual social capital are more likely to experience depressive symptoms, even after controlling for age, gender, and socioeconomic status. At the national level, countries with lower average social capital – such as Albania, Brazil, and Malaysia – report higher depressive symptom rates, compared to countries like Germany and Switzerland. Importantly, even after excluding high-prevalence countries, the link between low cognitive and behavioral social capital remained significant. Further evidence from China supports these findings, Dai & Gu (2022), using China Family Panel Studies (CFPS), found that individuals reporting mutual trust and assistance have significantly better mental health outcomes, with active social networks further enhancing mental health. In Great Britain, Bamford *et al.* (2021) found that neighborhood-level social capital generally improved mental health across ethnic minority groups, although the magnitude of the effect varies by socioeconomic and demographic factors, particularly among Indian and Pakistani groups. Likewise, Levesque & Quesnel-Vallée (2019) demonstrated gender-specific differences in the relationship between social capital, self-rated mental health, and heavy episodic drinking among Indigenous populations of Canada.

Evidence from developing countries further supported the dual universal and context-specific impacts of social capital. De Silva *et al.* (2007) reported that cognitive social capital reduces the likelihood of common mental health disorders across Peru, Ethiopia, Vietnam, and Andhra Pradesh in India, pointing to a broadly protective role. By contrast, structural social capital appears more culturally specific: Ethiopia, for example, reported higher rates of civic engagement than other countries. Additional studies illustrated these nuances. Among Vietnamese mothers of children with disabilities, social capital elements such as living in a mountainous area, having a “reserved” personality, and engaging in certain community activities are linked to better mental health, while participation in activism or political protests is associated with reduced benefits (Thi Minh Thuy & Berry, 2013).

The role of civic engagement has been also examined in post-conflict contexts. In a longitudinal study on sociotherapy in Rwanda, Verduin *et al.* (2014) found that civic participation increased by 7% in the intervention group compared to 2% in controls, with corresponding improvements in mental health of 10% versus 5%. However, changes in cognitive social capital and perceived support are less consistent. Workplace studies also stressed the relevance of social capital. In Brazil, Pattussi *et al.* (2016) found that workplace social cohesion exerts direct and indirect protective effects on mental health and health-related behaviors, reinforcing the idea that professional environments play a key role in sustaining well-being. Similarly, Cao *et al.* (2022) highlighted that in China, higher social capital and income are linked to fewer depressive symptoms and greater subjective well-being. Notably, family-based social capital in urban areas and community-level social capital in rural settings prove particularly beneficial for low-income individuals, suggesting that social engagement can mitigate mental health disparities.

Yet the relationship is not unidirectional. Labenbaum *et al.* (2021) observed that mental health challenges negatively impact social capital, by reducing individuals' sense of belonging and workplace support. This bidirectional perspective emphasizes the need for mental health policies that not only focus on prevention and treatment, but also actively sustain and strengthen social connections as a pathway to resilience.

1.4 Contextual framework

1.4.1 Mental health in Brazil

Globally, Brazil ranks fifth in cases of mental health disorders per 100 people, with 19.4% of the population affected by these conditions (IHME, 2024). Within the Americas, Brazil leads in Years Lived with Disability (YLD) due to mental disorders, which account for 36% of the total burden

(PAHO, 2018). Anxiety is the most prevalent mental health disorder in the country, affecting 18.6 million people – equivalent to 9.3% of the population – making Brazil the global leader in anxiety disorder prevalence. Anxiety contributes 7.5% of the country's YLD (PAHO, 2018). Depression follows as the second most prevalent disorder. According to IBGE and the Ministério dos Direitos Humanos e da Cidadania (MDHC), the proportion of individuals diagnosed with depression rose sharply from 7.6% in 2013 to 10.2% in 2019, marking a 34% increase and affecting approximately 16.3 million individuals. Women are diagnosed at a rate 2.8 times higher than men. While the highest prevalence is found among individuals aged 60-64 years (13.2%), the greatest proportional increase occurred among young adults aged 18-29, with a 51% rise in diagnoses (MDHC, 2022). Mental disorders account for roughly 13% of Disability-Adjusted Life Years (DALYs) in Brazil, with depression ranked as the fourth leading cause. Although less prevalent, schizophrenia and bipolar disorders still contribute significantly, accounting for 1.6% and 1.4% of YLD, respectively (PAHO, 2018; 2021).

Among other risk behaviors linked to mental health conditions, there are the abuse of alcohol and drug, interpersonal violence, and suicide. Alcohol and drug use emerged as a leading behavioral risk factor for disease burden in Brazil, particularly among men. Its contribution to DALYs increased significantly – from 7.4% in 1990 to 12.2% in 2016 – making it the top risk factor for males by that year (Marinho *et al.*, 2018). Exposure to violence and trauma is a major another concern for mental health in Brazil, with studies reporting that 35% of individuals in Rio de Janeiro and 21% in São Paulo have experienced traumatic events. These experiences are closely linked to the development of mental health disorders, underscoring the powerful influence of social, environmental, and cultural conditions on mental health outcomes (Razzouk *et al.*, 2020).

Finally, suicide represents another critical public health concern, with rates steadily increasing over the past two decades, raising from 5.1 deaths per 100,000 inhabitants in 2009 to 6.9 in 2009. The suicide rate is much greater among men than women: 11.4 per 100,000 males and 3.9 per 100,000 females (WHO, 2024). Despite global declines, Brazil saw a rise in suicide rates by 2022 among male adults (9.59 per 100,000), the elderly (8.60 per 100,000), and Indigenous peoples who were the most affected with 16.58 per 100,000 (Oliveira Alves *et al.*, 2024).

1.4.2 Brazilian Psychiatric Reform

The first psychiatric reform movement in Brazil began in 1979 with the Mental Health Workers' Movement. This movement laid the foundation for Brazil's Anti-Asylum Movement, which advocated for the social reintegration of institutionalized individuals and critiquing the asylum-based model. The Brazilian democratic transition of 1980s with the promulgation of the 1988 Constitution and the creation of the 1990 Unified Health System (*Sistema Único de Saúde* – SUS) boosted mental health policies which started to emphasize the respect of civil rights alongside health rights, supporting the citizenship of individuals with mental conditions. Various conferences such as Caracas Declaration (1990) and the Mental Health Coordination (1991) reinforced Brazil's commitment on decentralization and community-centered mental health care (Amarante, 1995; Sampaio & Bispo Júnior, 2021).

Since becoming public policy in 1992, the Brazilian Psychiatric Reform has followed an anti-asylum approach inspired by Franco Basaglia's vision, which arose in the 1960s. Rooted in the Italian democratic psychiatry movement, this perspective called for a humanized model of care, the transformation of asylums into therapeutic communities, and the social reintegration of individuals with mental health conditions (Amarante, 1995; Desviat, 2015). Between 1990 to 2010, Brazil's Psychiatric Reform Movement advanced toward the creation of Psychosocial Care Centres (*Centro de Atenço Psicossocial* – CAPS), therapeutic residential services, social interaction centres, and other facilities. Key legislative measures during this period included Law No. 10.216/2001, known as the Psychiatric Reform Law, which redefined the mental health care model and guaranteed the rights of individuals with mental health conditions.

The Ministério da Saúde provides mental health services through the *Rede de Atenção Psicossocial* (RAPS), a public healthcare network integrated into the SUS. RAPS ensures universal, comprehensive, and equitable mental health care, particularly for individuals experiencing psychological distress. A key component of RAPS is the CAPS, which provide specialized, community-based mental health services, replacing the traditional asylum model. The CAPS service was established under Ordinance MS/GM No. 336/2002, while Law No. 11.343/2006 established the National System of Public Policies on Drugs (SISNAD), promoting harm reduction and prevention as core principles in the care of psychoactive substance users (Fortes Monte Franklin & Borges, 2022). CAPS offers psychotherapy, psychiatric follow-ups, occupational and family therapy, neuropsychological rehabilitation, and medical management. These centers cater primarily to individuals with severe and persistent mental disorders, ensuring free, community-based care that fosters well-being and social integration. CAPS is divided into three specialized units: CAPS GERAL (general mental health care for individuals with severe mental disorders), CAPS AD (specialized treatment for substance use disorders, including drug and alcohol addiction), and CAPS INFANTIL (mental health services tailored for children and adolescents) (Ministério da Saúde, 2025a).

In following years, these reforms led to a drastic reduction in the number of psychiatric hospitals – from 87,134 beds in 1994 to 25,097 in 2016 – alongside a significant increase in community mental health services, with the number of CAPS rising from increased from 424 in 2004 to 3,013 in 2018 (Razzouk *et al.*, 2020). Furthermore, in 2006, there was a shift in funding from hospital-based to community-based mental health services, resulting in cost reductions in hospital admissions and improved care conditions (Alves Guimarães & Santos Rosa, 2019).

From 2016 to 2022, Brazil's mental health and drug policies shifted significantly away from the core principles of the Psychiatric Reform. Driven by an ultraliberal agenda of austerity and reduced state involvement, reforms restructured RAPS by reintegrating psychiatric hospitals, expanding funding for specialized institutions, and promoting abstinence-based approaches – particularly through the rise of Therapeutic Communities (TCs) (Sampaio & Bispo Júnior, 2021). These TCs often operate without qualified technical staff and create a problematic public-private overlap, diverting resources from CAPS and other public services (Alves Guimarães & Santos Rosa, 2019). Decrees No. 9.761/2019 and No. 9.926/2019 further institutionalized this shift by increasing funding to TCs and excluding civil society from drug policy governance. In addition, Technical Note No. 11/2019 reintroduced electroconvulsive therapy funding and allowed psychiatric hospitalization for children and adolescents (Sampaio & Bispo Júnior, 2021). These changes marked a return to a disease-centered, institutional model, undermining the Psychiatric Reform's principles of autonomy, inclusion, and rights-based care and placing at risk the progress made toward a more community-centered and more human mental health system.

1.5 Research question

This study quantitatively explores how social capital influences subjective happiness among individuals with different levels of mental health vulnerability, in an economically and socially fragile peripheral neighborhood in Fortaleza, Brazil.

Using structured questionnaires, 511 interviews were conducted with participants classified into three distinct mental health groups: (*i*) individuals with psychological conditions but no clinical psychiatric diagnosis (MSM); (*ii*) individuals receiving psychiatric treatment (CAPS); and (*iii*) individuals without diagnosed mental health conditions and not undergoing therapy (SEM). Despite sharing the same geographical environment, these groups differ significantly in socioeconomic status, mental health profile, and subjective well-being. Group categorization is based on clinical characteristics and participation in psychological or psychiatric therapies provided by local healthcare facilities. The SEM group represents the control group and the baseline in this research.

Individuals living with mental health conditions often face vulnerable situations, including stigma, social exclusion, and limited access to community, cultural engagement, and public health resources (Baxter *et al.*, 2022; WHO, 2022a). These outcomes are frequently shaped by broader structural issues, such as the absence of inclusive social policies and underinvestment in mental health infrastructure. Specifically, Brazil's peripheral neighborhoods report high levels of poverty, financial instability, inequality, limited access to care, and exposure to violence (IPEA, 2021). These conditions not only intensify mental health difficulties but also shape how individuals develop and maintain social ties, which in turn influence their well-being and life satisfaction.

As outlined in the previous sections, a large research has consistently shown that social capital can influence mental health outcomes (De Silva *et al.*, 2007; Connel *et al.*, 2014; Backhaus *et al.*, 2020) and subjective well-being (Bartolini, 2011; Rodríguez-Pose & von Berlepsch, 2014; Pancheva & Vásquez, 2022), showing that social capital buffers psychological conditions and promotes quality of life. However, most existing studies focus on the general population or specific subgroups such as older adults (Welsh & Berry, 2009; Luo *et al.*, 2020; Yen *et al.*, 2022; Monteiro *et al.*, 2024) or only on people with depressive symptoms (Park, 2009; Triphathi & Samanta, 2023), often in high-income countries (Ihlebæk *et al.*, 2023).

Although social capital is widely acknowledged as a protective factor for mental health, its moderating effect across different levels of mental health severity and treatment engagement related to happiness and well-being remains underexplored. Much of existing literature centers on specific symptoms or isolated dimensions of social capital. For instance, Adams *et al.* (2016) found that social support buffers the negative impact of depressive symptoms on life satisfaction among older adults, with strong networks preserving higher well-being under psychological distress. Other studies explored the cognitive dimension of social capital – including trust, reciprocity, and mutual respect – as a pathway to improved psychological well-being through emotional support and stress buffering (Giordano & Lindstrom, 2010; Han, 2015). However, the role of social capital to address mental health inequality – particularly in low- and middle-income countries – has received limited attention. In China, Cao *et al.* (2022) found that family-level social capital reduces disparities in depressive symptoms, while village-level capital buffers inequalities in subjective well-being. Similarly, Fei *et al.* (2023), examining economically motivated domestic migrants, reported that social capital significantly moderates the relationship between social integration and subjective well-being (β = 0.152, $p < 0.001$), and between physical health and subjective well-being (β = 0.148, $p < 0.01$), but not between mental health and subjective well-being ($\beta = 0.032$, $p > 0.05$). Additionally, Kapeli *et al.* (2024), using cross-lagged regression modelling on data from adult Pacific peoples in Aotearoa New Zealand, found that higher levels of social support correspond to a lower likelihood of experiencing psychological distress in the future.

In Brazil, empirical research on the relationship between social capital and well-being remains limited. Borges *et al.* (2010) demonstrated that behavioral, bridging, and cognitive aspects of social capital are associated with better self-rated health among adolescents. Ribeiro (2015) found that while material resources contribute to happiness, relational factors – such as social connections – have an even stronger influence on the likelihood of being happy. De Camargos *et al.* (2021) emphasized the role of lifestyle and the absence of psychological or psychiatric diagnoses in influencing happiness and life satisfaction. Soares *et al.* (2022) identified a positive relationship between trust, social norms, interpersonal networks, and well-being. Zanon *et al.* (2024) examined the role of social support during the COVID-19 pandemic in Brazil, showing that social support had a significant impact on mental health: while emotional support was linked to lower psychological distress, instrumental support was linked with higher distress, with self-reported happiness partially mediating these relationships. Despite these contributions, existing studies do not distinguish between psychiatric and psychological conditions, nor do they explore access to mental health services as a mediating factor.

This study addresses this gap by investigating the therapeutic role of social capital in shaping subjective happiness among individuals with different levels of mental health conditions within vulnerable urban settings. In this research, social capital is defined as a composite measure of frequency of social interactions, quality of interpersonal relationships, social inclusion, and participation or involvement in community activities. Subjective happiness, in turn, emphasizes living a valuable and meaningful life in line with the *eudaimonic perspective*.

The study emphasizes the heterogeneity of mental health care systems by distinguishing, firstly, across different levels of mental health severity and, secondly, between individuals receiving treatment in psychiatric public services (CAPS) and those participating in psychological or community-based therapies through civil society organizations (MSM). This distinction allows for a more precise analysis of how social capital interacts with the severity of mental health conditions and the type of care received.

To explore these relationships, the following research hypotheses are proposed:

H-1: Individuals with higher levels of social capital report significantly greater subjective happiness compared to those with lower levels.

H-2: Social capital moderates the negative effects of mental health conditions on happiness; even in presence of such conditions, individuals with higher social capital are expected to report higher happiness.

H-3: The effect of social capital on happiness varies across mental health treatment groups. The strongest positive effects are expected among MSM and CAPS participants, whereas the influence is weaker among SEM individuals, who are not engaged in any form of mental health treatment.

These findings have practical implications for the development of community-responsive mental health interventions tailored to individuals' needs, treatment context, and available resources, aligning with broader public health strategies aimed at prevention, integration, and equity in care delivery (Patel *et al.*, 2018). Such interventions are particularly crucial in settings where formal services are fragmented, underfunded, overloaded, or inaccessible to large segments of the population. By distinguishing between MSM and CAPS healthcare groups, this study not only contributes to a deeper theoretical understanding of the role of social capital in mental health dynamics, but also frames its therapeutic relevance through differentiated responses – ranging from preventive strategies for SEM individuals, to integrative psychosocial support for MSM, and multidisciplinary care for CAPS – with the aim of enhancing well-being in vulnerable urban and peripheral areas of Fortaleza.

1.6 Data

1.6.1 Study design and data collection

This observational study took place in Grande Bom Jardim (GBJ), a peripheric neighborhood in Fortaleza, Ceará, Brazil, from January to April 2023. Face-to-face interviews were carried out using a standardized survey questionnaire, ensuring voluntary participation, anonymity, and confidentiality. The research was supported by CAPS GERAL - REGIONAL V and Movimento de Saúde Mental (MSM), both operating in the same residential area. Data collection adhered to ethical guidelines, respecting privacy, dignity, and voluntary consent. Before each interview, participants received a privacy consent form detailing the study's purpose, scope, duration, and confidentiality measures. No medical records were accessed; all health-related data were self-reported. Interviews were conducted in designated facility areas, either before or after treatments or medical consultations. To build trust, the researcher was introduced by local staff and participated in various group therapy sessions. For non-patients, the survey was administered via paper questionnaires or Google Forms, both following the same format. All responses were digitally stored, while paper versions securely archived. Anonymity and data protection were ensured, with access restricted to the researcher and designated local operators. The digital archive is protected by an alphanumeric password.

1.6.2 Sampling strategy

Three distinct groups were identified for this study. Respondents were randomly selected among adults attending therapy sessions, and group assignment was based on their mental health condition and type of therapy. Individuals who could not understand the survey's purpose and questions, or who were unable to respond either independently or with assistance, were excluded from the sample.

1° group – This group includes individuals with severe mental health conditions. Observations were conducted at CAPS GERAL – REGIONAL V, which serves the Secretaria Regional V (SER V), a southern region with 19 neighborhoods and a population of 596,987 (IBGE, 2010). By December 2022, internal CAPS data reported 16.957 patient records – about 3% of the total SER V population. These records refer exclusively to CAPS users undergoing psychiatric and pharmacological treatment, and excluding patients treated in private facilities. In 2022, 1,269 new users were registered (65,0% female, 34,9% male). No disaggregated information is available on the distribution of specific mental illnesses.

2° group – This group includes users of the Movimento de Saúde Mental (MSM). According to its 2022 report, MSM assisted 10.760 individuals in 2021, providing therapy, food distribution, social work, and vocational training. By the end of 2022, 436 new patients had joined, of whom 75.2% were female, 24.5% male, and the reminder identified otherwise.

MSM supports users of CAPS GERAL – REGIONAL V as well as individuals with moderate to low levels of mental health severity. Those included in this group were selected based on their participation in MSM activities and their non-severe conditions without psychiatric follow-up. Diagnoses typically involve stress, anxiety, borderline personality disorder, PTSD, panic attacks, low self-esteem, and other similar disorders.

Founded in 1996, by the Combonian Missionaries, MSM is a community-based movement that has since supported over 5,000 individuals and reached about 325,000 people through 15 active projects across 13 locations (MSM, 2025). In line with Ministério da Saúde guidelines (2025b), MSM integrates PICS (*Práticas Integrativas e Complementares em Saúde* – Integrative and Complementary Practices for Health), which aim to prevent disorders and promote well-being through therapeutic relationships and social integration. Activities include integrative community therapy, self-esteem groups, massage therapy, memory development workshops, meditation, art therapy, music therapy, phytotherapy, and gastronomy courses (MSM, 2022). These practices are rooted in the Community Systemic Approach (*Abordagem Sistêmica Comunitaria* – ASC), a multidisciplinary socio-therapeutic framework that combines individual and group interventions to foster mental health, strengthen community identity, and build self-esteem and resilience (Bonvini, 2023).

3° group – The third group serves as the control group, consisting of GBJ residents without psychological or psychiatric diagnoses related to mental disorders. Its inclusion is essential to establish a baseline for external shocks and potential confounding factors that might bias the findings. By representing the "zero baseline" on the mental health spectrum, this group allows for clearer differentiation between outcomes directly linked to mental health conditions and those shaped by socioeconomic status, environmental factors, or personal characteristics.

Comparing individuals across groups, while controlling for relevant confounders, helps identify whether observed differences are truly attributable to severity of mental health disorder. At the time of the interview, participants in this group were neither receiving pharmaceutical therapy for mental disorders nor engaged in psychological therapy. Although this does not entirely rule out undiagnosed conditions, it ensured that only individuals not actively involved in psychiatric or psychological treatment were included in the control sample.

1.6.3 Survey questionnaire

An *ad hoc* questionnaire was developed for this research and is presented in the Appendix (Table A.1). The survey combined multiple-choice questions with Likert scales items and was designed to be accessible to participants with low educational levels, mental health disorders, or limited confidence. To ensure clarity, the questionnaire was simplified and adapted for self-completion. Local operators contributed to refining the questionnaire by suggesting modifications, additions, and removals of items to better suit the target population. Before fieldwork, a pilot study with a small group of respondents was conducted to evaluate clarity and comprehension. This pilot participants were excluded from the final sample.

The questionnaire comprises 18 questions divided into three sections: personal profile, self-reported health, and social capital.

The first section gathers demographic and individual characteristics, including gender, age, ethnicity, marital status, occupational status, education level and the number of technological devices available at home.

The second section focuses on self-reported health conditions, as access to medical records was not available. General health was assessed using a 1-4 Likert scale, while mental health symptoms were measured on 1-5 Likert scales capturing their intensity in the month prior to the interview. The mental health items were adapted from the Center for Epidemiological Studies-Depression (CESD) and the Brief Symptom Inventory (BSI) (Derogatis & Melisaratos, 1983; Rath & Fox, 2010; Abraham *et al.*, 2017). The scale, ranging from 1 – "Never" to 5 –"Everyday", recorded the frequency and intensity of symptoms such as depression, anxiety, nervousness, tiredness, disability, and stress (Andresen *et al.*, 1994; Spitzer *et al.*, 2006).

The third section explores subjective happiness and social capital dimensions, specifically social inclusion, social bonding, social participation, volunteering, and trust in institutions. Subjective happiness, the dependent variable of the study, was captured using a 4-point Likert scale designed to evaluate psychological well-being, particularly in populations with specific needs (Hills & Argyle, 2002; World Values Survey, Wave 6, 2010–2014).

Social inclusion was measured using a 4-point Likert, assessing feelings of community belonging and social acceptance (Baumgartner & Burns, 2013). Social bonding referred to the quality and nature of interpersonal relationships and was assessed through two measures: network size (number of friends) and social support (frequency of meetings with friends) (Veenhoven, 2008; Cornwell & Waite, 2009). Previous studies have shown that larger social networks (Demir, 2015) and regular social interaction (Kislev, 2020) positively influence happiness and well-being.

Social participation captured involvement in public events, social gatherings, local meetings, and community activities organized by associations, civil society groups, social clubs, and religious institutions. Participation fosters social connections and a sense of belonging (Lochner *et al.*, 1999; Veenhoven, 2008; Hashidate *et al.*, 2021). Volunteering serves as an additional measure of participation, reflecting active engagement in activities, programs, and projects that support and improve the community (Stone, 2001; Stone & Hughes, 2002; Ejlskov *et al.*, 2014). The positive role of volunteering in enhancing well-being is well documented (Dolan *et al.*, 2021), although findings remain mixed. For example, Lee (2019) and Krasnozhon & Levendis (2020) initially found a positive association between volunteering and happiness, but the results became non-significant after adjusting for personality traits, trust, and health in the first study, and for socioeconomic factors in the second. Overall, however, participation through volunteering has been shown to increase life satisfaction and feelings of worthwhileness.

Trust in institutions was measured through six dimensions: trust in church, school, police, press, national government, and local authorities. Responses were rated on a 5-point Likert scale ranging from 1 – “Not trust at all” to 5 – “A lot of trust” (Naef & Schupp, 2009; Carillo Álvarez & Romaní, 2017).

Finally, the survey was designed to ensure maximum freedom of response and anonymity, in line with ethical principles, human integrity, and individual dignity. The research project and survey were submitted to ethical review by CaREUS (Comitato per la Ricerca Etica nelle scienze Umane e Sociali) of the University of Siena, which issued a positive opinion (n. 70, 2022) on December 23, 2022. No further submissions have been made.

1.7 Descriptive statistics

A total of 511 interviews were conducted, of which 502 valid responses were retained after excluding incomplete or missing data. The sample was drawn from three distinct groups: SEM with 160 observations (31.9%), MSM with 135 observations (26.7%), and CAPS with 207 observations (41.3%). All variables are categorical, and the Anderson-Darling test confirmed that the assumption of normality is not met. The three groups were randomly selected from their respective populations, and the study design ensured controlled conditions to verify the assumption of independence.

1.7.1 Demographic and socioeconomic characteristics

Table 1.1 presents the socio-demographic and socioeconomic characteristics of the three groups. Overall, 75.7% of respondents are female, with proportions of 74.4% in CAPS, 85.2% in MSM, and 69.4% in SEM. Age is distributed across six categories: 18–25 years (12.3%), 26–35 years (17.7%), 36–45 years (23.3%), 46–55 (24.1%), 56–65 years (16.3%), and over 65 years (6.2%). SEM respondents tend to be slightly younger than those in the other groups, showing a greater concentration in the younger brackets. Regarding ethnicity, 81.9% of participants identify as Black, light-skinned Black, or Indigenous, while 18.1% identify as White. Marital status also differs with only 29% of CAPS respondents are married, compared to 43.7% in MSM and 45.6% of SEM.

Socioeconomic status was assessed through three key indicators: occupational status, educational level, and financial well-being. Employment data reveal that 53.2% of the total sample were employed, while 10.1% were retired. Across groups, CAPS respondents report the lowest employment rate (38.2%), compared to 65.6% in SEM and 61.5% in MSM. Educational attainment also varies: 41.8% of the overall sample have only elementary education or less. This share rises to 50.2% in CAPS (including respondents with no formal schooling), compared to 37.8% in MSM and 34.3% in SEM. Financial well-being follows a similar pattern. 70% of CAPS respondents report severe financial difficulties or no personal income, compared to 51.9% in MSM and 45.6% in SEM. Disparities are also evident in technological access. Measured by the number of digital devices at home, SEM respondents show the highest access, while CAPS and MSM participants report substantially lower levels.

Subjective happiness – the dependent variable – mirrors these socioeconomic inequalities. SEM respondents report the highest average score ($M = 3.450$), reflecting greater overall well-being. MSM participants follow with a moderate mean level of 3.015. In contrast, CAPS respondents record the lowest average ($M = 2.522$), steady with the socioeconomic disadvantages observed above and indicating greater economic and social vulnerability in this group.

Table 1.1: Descriptive statistics

	SEM (n = 160)		MSM (n = 135)		CAPS (n = 207)		Total (n = 501)		
Variables	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*Min/Max*
Gender (female)	0.694	0.462	0.852	0.357	0.744	0.437	0.757	0.429	0/1
Age									
18-25	0.138	0.345	0.089	0.286	0.135	0.343	0.123	0.329	0/1
26-35	0.206	0.406	0.156	0.364	0.169	0.376	0.177	0.382	0/1
36-45	0.231	0.423	0.237	0.427	0.232	0.423	0.233	0.423	0/1
46-55	0.256	0.438	0.274	0.448	0.208	0.407	0.241	0.428	0/1
56-65	0.106	0.309	0.156	0.364	0.256	0.438	0.181	0.386	0/1
Over 65	0.063	0.243	0.089	0.286	0.000	0.000	0.044	0.205	0/1

Black, light-skinned black, indigenous	0.863	0.345	0.807	0.396	0.792	0.407	0.819	0.386	0/1
Married	0.456	0.500	0.437	0.498	0.290	0.455	0.382	0.486	0/1
Occupational status (employed)	0.656	0.476	0.615	0.488	0.382	0.487	0.532	0.499	0/1
Retired	0.063	0.243	0.089	0.286	0.140	0.348	0.101	0.302	0/1
Financial well-being	2.487	1.093	2.400	1.073	1.937	1.062	2.237	1.102	1/4
No personal income	0.262	0.441	0.267	0.443	0.478	0.501	0.353	0.478	0/1
Severe financial hardship	0.194	0.396	0.252	0.436	0.222	0.417	0.221	0.415	0/1
Moderate financial hardship	0.337	0.474	0.296	0.458	0.184	0.388	0.263	0.441	0/1
No financial hardship	0.206	0.406	0.185	0.390	0.116	0.321	0.163	0.370	0/1
Education level	2.706	0.969	2.652	0.840	2.295	0.963	2.522	0.951	1/4
No formal schooling	0.156	0.364	0.104	0.306	0.280	0.450	0.193	0.395	0/1
Elementary school	0.188	0.392	0.274	0.448	0.222	0.417	0.225	0.418	0/1
Secondary school	0.450	0.499	0.489	0.502	0.420	0.495	0.448	0.498	0/1
University or more	0.206	0.406	0.133	0.341	0.077	0.268	0.133	0.340	0/1
Technological access	3.100	0.870	3.059	0.870	2.768	0.916	2.952	0.901	1/4
Subjective happiness	3.450	0.680	3.015	0.881	2.522	0.975	2.950	0.950	1/4

As presented in Table 1.2, clear differences emerge across the three groups in general health perception and mental health symptoms. CAPS coherently reports the poorest outcomes, while SEM shows the most favorable indicators, followed by MSM. For self-reported general health, the SEM (M = 3.375) and MSM (M = 3.133) groups display higher mean scores, implying a more positive perception of overall health. In contrast, the CAPS group records the lowest score (M = 2.565), reflecting more severe health limitations or chronic conditions. Similar patterns appear in mental health. CAPS participants report the highest mean values for depression, anxiety, and stress, pointing to greater psychological distress. MSM respondents also experience notable, though less severe, difficulties, whereas SEM participants present the most positive profile overall.

Table 1.2: Descriptive statistics for self-reported health

	SEM (n = 160)		MSM (n = 135)		CAPS (n = 207)		Total (n = 501)		
Variables	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*Min/Max*
Self-reported general health	3.375	0.601	3.133	0.845	2.565	0.952	2.976	0.898	1/4
Mental health symptoms									
Tiredness	2.425	0.929	2.696	1.135	3.411	1.285	2.904	1.220	1/5
Disability	2.200	1.228	2.511	1.263	3.184	1.287	2.689	1.331	1/5
Insomnia	2.187	1.106	2.963	1.289	3.918	1.152	3.110	1.388	1/5
Fatigue	2.369	0.962	3.000	1.165	3.560	1.217	3.030	1.234	1/5
Depression	1.850	0.992	2.800	1.190	3.585	1.187	2.821	1.346	1/5
Anxiety	2.644	1.072	3.452	1.151	4.010	1.043	3.424	1.226	1/5
Nervousness	1.981	1.000	2.837	1.229	3.415	1.191	2.803	1.294	1/5
Concentration	2.237	1.049	2.719	1.111	3.483	1.218	2.880	1.256	1/5
Stress	2.444	0.976	3.252	1.111	3.551	1.173	3.118	1.194	1/5

Table 1.3 presents the distribution of social capital dimensions across the three groups, including friendship, social meetings, social participation, volunteering, and trust in institutions.

In terms of friendship networks, CAPS respondents report the fewest friendships (M = 2.39), compared to 2.93 in MSM and 3.00 in SEM. This suggests that CAPS participates tend to have smaller social networks. A similar pattern is observed for social meetings. CAPS records the lowest mean (M = 1.84), followed by MSM (M = 2.09) and SEM (M = 2.16). These findings indicate that CAPS respondents meet their contacts less frequently than individuals in the other groups.

For social participation, CAPS again reports the lowest level of engagement (M = 1.78). MSM respondents score slightly higher (M = 1.97), while SEM falls in between (M = 1.90). This comparison indicates that CAPS participants are less involved in public and community activities.

Levels of volunteering are relatively low across all groups, but remain lowest among CAPS respondents, with only 31% engaged in community-oriented activities. In comparison, 48% of both MSM and SEM participants report volunteering, indicating that community engagement is more common outside the CAPS group.

Regarding social inclusion, SEM respondents report the highest mean score (M = 3.375), reflecting a stronger sense of belonging and community. MSM follows closely (M = 3.326), while CAPS records the lowest mean score (M = 2.860), suggesting greater risks of social exclusion and isolation among individuals with more severe mental health conditions.

Finally, differences emerge in trust in institutions. CAPS respondents report the highest trust in several institutions, including church (M = 3.47), police (M = 2.80), press (M = 2.85), national government (M = 2.83), and local authorities (M = 2.72). However, trust in school is lower in CAPS (M = 3.30), compared to MSM (M = 3.57) and SEM (M = 3.68). This alludes to the fact that while CAPS participants tend to place more confidence in religious, governmental, and local public institutions, they are comparatively less trusting of educational institutions.

Table 1.3: Descriptive statistics for social capital variables

	SEM (n = 160)		MSM (n = 134)		CAPS (n = 207)		Total (n = 501)		
Variables	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*Min/Max*
Friendships	3.044	0.941	2.926	0.943	2.386	1.068	2.741	1.039	1/4
Social meetings	2.163	0.816	2.096	0.800	1.841	0.875	2.012	0.848	1/3
Social participation	1.900	0.803	1.970	0.846	1.783	0.890	1.870	0.853	1/3
Volunteering	0.481	0.501	0.481	0.502	0.314	0.465	0.412	0.493	0/1
Social inclusion	3.375	0.874	3.326	0.845	2.860	0.983	3.149	0.943	1/4
Trust in institutions									
Trust in church	3.394	1.259	3.459	1.297	3.469	1.332	3.442	1.298	1/5
Trust in school	3.688	1.065	3.578	1.061	3.304	1.262	3.500	1.159	1/5
Trust in police forces	2.781	1.120	2.741	1.065	2.802	1.232	2.779	1.152	1/5
Trust in press	2.719	0.953	2.741	1.044	2.855	1.230	2.781	1.098	1/5
Trust in national government	2.669	1.153	2.704	1.159	2.831	1.237	2.745	1.190	1/5
Trust in local authorities	2.638	0.908	2.637	0.951	2.725	1.131	2.673	1.015	1/5

1.7.2 Kruskal-Wallis and Dunn's test

Since the assumption of normality is not satisfied, the Kruskal-Wallis test – a non-parametric alternative of ANOVA – was applied to evaluate whether the medians of three groups differs significantly, and whether at least one group stochastically dominates another (Kruskal & Wallis, 1952). When the *p-value* for a variable is below 0.05, the null hypothesis H_0 is rejected, indicating significant differences in group medians and suggesting that at least one group differs from the others. As reported in the Appendix (Table A.2), the Kruskal-Wallis test reveals substantial differences among the three groups for several variables.

To further examine these differences, a post hoc Dunn's test (Dunn, 1964) was conducted on variables that showed significance in the Kruskal-Wallis test. This analysis identifies significant pairwise differences between MSM-CAPS, SEM-MSM, and CAPS-SEM. The results show that distributions of gender, marital status, occupational status, retirement, financial well-being, education, and technological access differ notably across groups, particularly between CAPS and the other two groups. MSM and SEM, in contrast, display more similar distributions. Self-reported general health varies significantly across all groups, while mental health symptoms show clear differences without strong overlaps. Regarding social inclusion, only the SEM-MSM comparison shows a non-significant *p-value*, while subjective happiness differs substantially across groups. Significant differences also emerge in social capital indicators, including friendships, social meetings, volunteering, and trust in school, with the strongest contrasts observed between CAPS and both MSM and SEM.

In summary, SEM and MSM groups exhibit similar characteristic, whereas CAPS respondents differ significantly, particularly in terms of socioeconomic status, health outcomes, and social capital. These findings reflect the distinct roles and vulnerabilities of each group, underlining the importance of addressing the underlying social determinants that shape such disparities.

1.7.3 Exploratory Factor Analysis

A set of independent variables was used to explore the relationship between social capital, mental health, and subjective happiness. To detect potential latent constructs underlying these variables, an Exploratory Factor Analysis (EFA) was conducted. EFA is a statistical technique that identifies hidden structures among observed variables and reduces dimensionality, thereby uncovering complex data patterns (Yong and Pearce, 2013).

Because the items in this study were measured categorically, ordinally, and with Likert scales, the analysis was based on a *polychoric* correlation matrix. As noted by Holgado *et al.* (2010), this method is preferable to Pearson correlations when variables data are ordinal, binary, or non-normally distributed. The *polychoric* approach assumes that observed categorical responses reflect underlying continuous, normally distributed latent traits, and estimates correlations among these latent constructs. This makes it particularly suited for items with fewer than 5–7 categories or asymmetric distributions (Watkins, 2018; Xia & Yang, 2019).

As described in the Appendix (Table A.3, Figure A.1), the EFA identified three latent factors, jointly explaining 47.6% of the cumulative variance:

The first factor (ML1) refers to mental health. The factor was constructed from the frequency of symptoms experienced in the previous month, including tiredness, disability, fatigue, insomnia, depression, anxiety, nervousness, concentration difficulties, and stress. This factor explains 26% of the total variance and was retained as the composite measure of mental health.

The second factor (ML2) refers to trust in institutions. It derived from six items, measuring trust in church, school, police, press, national government, and local authorities. This factor accounts for 11.9% of the variance, representing a broad dimension of trust in institutions.

The third factor (ML3) refers to social capital. This index was created from five items: number of friendships, frequency of social meetings, participation in neighborhood social events, volunteering, and feeling of social inclusion. This factor explains 9.7% of the variance.

To address potential confounders, several demographic and socioeconomic variables were included. Age was treated as an ordinal variable with five categories, after merging the oldest group (over than 65) with the fifth category 56-65 bracket to reduce sparse observations. Ethnicity was recoded as a dichotomous variable, distinguishing between Black/light-skinned Black individuals and White respondents. Education level and financial well-being were also included as additional controls.

1.8 Modeling strategy

To investigate the impact of social capital on subjective happiness, three modelling approaches were employed: a general model, a subsample model, and a cluster model. Each approach employs an Ordered Probit (OP) regression model, which is well-suited for modeling ordinal dependent variables. Since subjective happiness is measured on an ordinal scale, the OP model allows for the estimation of latent relationships while respecting the ordered nature of the outcome categories without assuming equal distances between them. To strengthen the robustness and interpretability of the findings, Ordinary Least Squares (OLS) regressions are also presented as complementary models.

The general model analyzes the full sample without distinguishing between mental health groups, providing an overall estimate of the relationship between social capital and happiness. In contrast, the subsample model stratifies the sample based on mental health severity tertiles – low, moderate, and high – allowing the analysis to capture how the relationship varies across levels of mental health distress. The cluster model further distinguishes individuals by mental health groupings based on clinical criteria: SEM group (individuals without diagnosed mental health disorders and not undergoing mental health therapy), MSM group (individuals with psychological distress and participating only to psychological therapies), and CAPS (individuals with diagnosed psychiatric conditions and psychiatric involvement).

According to results of the Exploratory Factor Analysis (EFA), the indicators of social capital and trust in institutions were included separately in the analysis. The relative effect of each item is presented in the regression estimates to show their distinct contributions to subjective happiness across mental health groups.

The objective of this modeling strategy is to first assess the average effect of social capital on happiness in the general population and then explore whether this relationship differs by mental health severity and status, reveling potential heterogeneity in effect size and statistical significance.

1.8.1 General model

The general model examines the overall effect of social capital (SC) and trust in institutions (IT) on subjective happiness (SH) across the full sample, with and without interactions with mental health (MH). Two specifications of the social capital variable were considered to allow comparison: a continuous index of social capital derived from EFA, and a binary indicator (Social capital$_{high}$) obtained by dichotomizing the continuous measure at the sample median. Respondents above the median were coded as 1 (*high social capital*), while those at or below were coded as 0.

Two specifications were considered for the general model:

(i) Direct effect of social capital

$$YSH_i = \alpha + \beta_1 SC_i + \beta_2 MH_i + \beta_3 IT_i + \sum_{k=1}^{K} \gamma_k X_i^{(k)} + \varepsilon_i$$

(ii) Interaction between social capital and mental health

$$YSH_i = \alpha + \beta_1 SC_i + \beta_2 MH_i + \beta_3 (SC_i \cdot MH_i) + \beta_4 IT_i + \sum_{k=1}^{K} \gamma_k X_i^{(k)} + \varepsilon_i$$

In specification (*ii*), β_1 captures the effect of social capital, β_2 represents the effect of mental health factor (ML1), β_3 measures whether social capital moderates the relationship between mental health and happiness, and β_4 refers to trust in institutions factor (ML2). $X_i^{(k)}$ represents the k^{th} control variables, and ε_i is the error term.

1.8.2 Severity-level subsample model

To explore heterogeneous effects, the sample was stratified into three levels of mental health severity – low, moderate, and high – based on tertiles of the mental health factor (ML1). In this stage, no interaction terms were included, and only the continuous measure for social capital was used in the models.

(iii) Direct effect of social capital

$$YSH_i = \alpha + \beta_1 SC_i + \beta_2 IT_i + \sum_{k=1}^{K} \gamma_k X_i^{(k)} + \varepsilon_i$$

Through this stratified approach, the analysis examines whether the role of social capital differs across increasing levels of mental health conditions and mental health symptoms.

1.8.3 Cluster-based model

To account for differences across mental health groups defined by treatment and diagnostic criteria, individuals are classified into three clusters as previously described:

- SEM: individuals without diagnosed mental health disorders and not receiving any treatment.
- MSM: individuals experiencing psychological distress and receiving only psychological therapy.
- CAPS: Individuals with diagnosed psychiatric conditions receiving psychiatric care.

Model specification (*i*) is then re-estimated separately for each cluster to assess whether the effects of social capital on subjective happiness vary across clinical mental health group. In these models, only the continuous measure of social capital is included, and no interaction terms are specified at this stage.

1.9 Balancing the model covariates

This study employed two treatment variables for social capital: a binary indicator representing *high social capital*, and a composite score for *continuous social capital*.

To address potential biases and mitigate the risk of inflated or spurious estimates, Propensity Score Matching was applied when the treatment was binary, and Nonparametric Covariate Balancing Generalized Propensity Scores were used for the continuous treatment. Both techniques correct covariate imbalance and mitigate selection bias in the assignment of social capital, rendering treatment assignment statistically independent of observed confounders. The balancing set included demographic characteristics (gender, age, ethnicity, marital status, retirement, employment status), socioeconomic indicators (financial well-being, education, access to digital technology), physical and mental health conditions (general health, tiredness, disability, insomnia, fatigue, depression, nervousness, concentration, and stress), and trust in institutions (church, school, police, press, national and local government). Diagnostics confirmed that mean differences across covariates are substantially reduced after weighting, with standardized differences approaching zero, thereby supporting the validity of the identification strategy. In addition, a subset of these covariates (gender, age, ethnicity, education level, financial well-being, and general health) was included as controls in the regression models. This regression adjustment aims to minimize residual imbalance and enhance robustness of the estimates.

Variables constituting social capital index – number of friends, sense of social inclusion, social participation, frequency of social interactions, and volunteering – were excluded from the balancing approach, as they form the core of the treatment construct itself. Including them would risk over-controlling and biasing the estimation.

Finally, given the absence of valid exogenous instruments, the balancing methods were applied across all model specifications – general, subsample (low-, moderate-, and high-severity mental health), and cluster models (SEM, MSM, and CAPS) – to enhance the robustness and interpretability of the causal claims.

1.9.1 Propensity Score Matching

Propensity Score Matching (PSM) is a statistical technique used to reduce selection bias in observational studies by matching treated and untreated individuals who have similar likelihoods (propensity scores) of receiving the treatment. These scores are based on observed covariates. By comparing individuals with similar propensity scores, PSM mimics aspects of a randomized experiment and allows for a more credible estimation of the Average Treatment effect on the Treated (ATT) (Austin, 2011). To address potential selection bias and improve causal inference with a dichotomous treatment variable, Propensity Score Matching (PSM) was performed using the `MatchIt` package in R (Ho *et al.*, 2011; Randolph *et al.* 2014). Although originally designed for experimental data, the package is commonly applied in observational studies where the treatment variable is not randomly assigned, or the random assignment may fail. Specifically, the nearest-neighbor matching with a caliper of 0.2 was employed, restricting matches to within a maximum allowable difference in propensity scores and thereby improving match quality and reducing bias (Rosenbaum & Rubin, 1985). The binary treatment variable was *high social capital*, constructed via a median split of the continuous social capital index. The propensity score was estimated using a logistic regression (Logit) model that included the set of covariates theoretically tied with both social capital and subjective happiness.

After matching, the covariate balance was assessed using standardized mean differences (SMD), with values below 0.1 considered acceptable, and visually inspected using balance plots. The results indicate that balance improved substantially post-matching, reducing the likelihood of confounding bias. Detailed diagnostics are reported in the Appendix (Table A.4).

1.9.2 npCBGPS

Nonparametric Covariate Balancing Generalized Propensity Scores (npCBGPS) is used to ensure robust covariate balance through empirical weighting in observational data with continuous and ordinal treatments – in this case, *continuous social capital* (Fong *et al.*, 2018). NpCBGPS was selected over parametric approaches as it does not impose strict functional form assumptions, handles nonparametric distributions, and enhances flexibility in balancing covariates. Unlike traditional Covariate Balancing Generalized Propensity Scores (CBGPS) (Imai & Ratkovic, 2014), which impose balance through moment conditions but rely on an assumed functional form, npCBGPS uses an empirical likelihood approach that offers greater flexibility in weighting and balance optimization. In this study, the method achieved a significant reduction in confounding, supporting a more credible interpretation of the causal effect of social capital on subjective happiness.

Following Fong *et al.* (2018) formulation, the npCBGPS weights (ω_i) are estimated as:

$$\omega_i = \frac{f(T_i^*)}{f(T_i^*|X_i^*)}$$

where $f(T_i^*)$ represents the marginal density of treatment variable and $f(T_i^*|X_i^*)$ represents the conditional density given covariates.

Unlike parametric approaches, npCBGPS does not impose a functional form on these densities, making it robust against model misspecification. The balancing condition is satisfied when:

$$E(\omega_i T_i^* X_i^*) = E(T_i^*)E(X_i^*) = 0$$

This condition ensures that, after weighting, the treatment assignment is statistically independent of covariates, thereby reducing confounding at the first-moment level. To obtain the final weights, npCBGPS solves an empirical likelihood optimization problem:

$$arg \min_{\omega \in \mathbb{R}^N} \sum_{i=1}^{N} log\omega_i$$

subject to balancing constraints on covariates and treatment interactions.

1.9.2.1 Selection of covariates for npCBGPS

Before performing covariate balancing, a systematic selection procedure was applied to identify meaningful covariates associated with both the outcome – subjective happiness – and the exposure – social capital. The goal was to enhance statistical efficiency by retaining confounders (X_c) and prognostic covariates (X_p), while excluding spurious (X_s) and instrumental covariates (X_i), reducing bias and improving estimation accuracy.

Given the skewed and non-normal distribution of subjective happiness, Generalized Median Adaptive Lasso (GMAL) was applied for covariate selection (Liu *et al.*, 2024). GMAL is particularly suited to high-dimensional observational data, as it prioritizes covariates strongly related to the outcome while down-weighting weaker predictors. It follows the Outcome Adaptive Lasso (OAL) framework, assigning penalty weights to covariates according to their contribution to the outcome (Shortreed & Ertefaie, 2017). Penalty weights are defined as:

$$\widehat{\omega}_j = |\widetilde{\beta}_j|^{-\gamma}, \gamma > 1$$

where $\tilde{\beta}_j$ is the median regression coefficient for the *j-th* covariate, and γ is a tuning parameter regulating penalization strength. Setting $\gamma > 1$ ensures that strongly associated covariates receive lower penalties, preserving their inclusion. Simulations evidence indicates that $\gamma = 2$ achieves optimal selection, minimizing overfitting while reducing the risk of omitting relevant predictors (Gao *et al.*, 2021).

The final adjustment set $X_c \cup X_p$ was derived using LASSO regression with 10-fold cross-validation, ensuring that only the most relevant covariates were retained. The regularization parameter λ, which controls the degree of sparsity in variable selection, was automatically with the `cv.glmnet()` function, with the optimal value (λ_{min}) chosen to minimize cross-validated error, striking a balance between bias and variance (Hastie *et al.*, 2025).

After this step, refinement was introduced using Dual-Weight Correlation (DWC), following Gao *et al.* (2021). While LASSO selects covariates predictive of the outcome, DWC prioritizes those that also reduce their weighted correlation with the treatment, thereby improving balance before weighting. This additional refinement ensures that the adjustment set maximizes predictive validity and treatment balance.

Balancing weights were then estimated through npCBGPS, which optimizes covariate balance directly without requiring explicit Generalized Propensity Score estimation. By relying on an empirical likelihood framework, npCBGPS ensures that, after weighting, the treatment is statistically independent of the covariates, producing more stable and less biased estimates. This approach strengthens the plausibility of causal inference in a non-randomized study.

1.9.2.2 Results for npCBGPS

The npCBGPS was implemented RStudio following the guidelines of Greifer (2024; 2025). The `weightit()` package was used to estimate balancing weights for the *continuous social capital* variable with a single exposure period, specifying `method = "npcbps"`. To limit the impact of extreme weights – which can inflate variance and compromise model stability – weights were trimmed at the 95th percentile, a standard practice in propensity score weighting (Lee *et al.*, 2011).

Covariate balance was assessed before and after weighting. As reported in the Appendix (Figure A.2, Figure A.3, Figure A.4, Figure A.5, Figure A.6, Figure A.7, Figure A.8, Figure A.9), visual diagnostics confirm a substantial reduction in covariate imbalance, with clear improvements after applying npCBGPS. The effective sample size (ESS) decreased slightly across all models, reflecting minor losses due to weighting, but remained sufficient to ensure robust estimation.

1.10 Empirical results

This section presents the results of the Ordered Probit (OP) regressions for the general, subsample, and cluster models.

Social capital demonstrated a strong positive association with subjective happiness across nearly all models. When models were stratified by mental health severity and status, the strength of this relationship varied, proposing a more complex interplay between social capital, mental health, and well-being. To improve internal validity and reduce estimation bias, npCBGPS and PSM were employed to correct covariate imbalance. The use of these techniques adjusted the coefficients while preserving their significance and direction. Estimated coefficients reflect variations in the latent dimension of subjective happiness. Their interpretation therefore concerns the direction and magnitude of the effect rather than outcome probabilities.

For comparison, unweighted OP and OLS regression results are reported in the Appendix (Table A.13, Table A.14, Table A.15, Table A.16, Table A.17, Table A.18), Table, allowing for an evaluation of how covariate balancing affects magnitude and precision of the results. Additionally, Variance Inflation Factor (VIF) tests revealed no multicollinearity among predictors, enhancing model validity and robustness.

Overall, the empirical evidence confirmed that social capital remains a key predictor of happiness across diverse mental health profiles. The effect of social capital on subjective happiness appears particularly relevant for individuals with moderate to severe psychological conditions (MSM and CAPS), where it functions as a protective and enhancing factor. In contrast, its role among individuals with low symptom severity or no diagnosis (SEM) appears more marginal, suggesting distinct mechanisms of well-being.

1.10.1 Results for general model

In the general model, two measures of social capital were used: a continuous index (Social capital) and a binary indicator (Social capital$_{high}$).

According to Table 1.4, social capital emerges as one of the most influential predictors of happiness. Although its estimated coefficients are slightly reduced after weighting, the effect remains robust. In Model 2, the coefficient for continuous social capital index declined from β = 0.395*** to β = 0.392***. Similarly, when using Social capital$_{high}$, the coefficient shifted from β = 0.515*** to β = 0.396*** in Model 4, while still maintaining statistical significance. Despite these adjustments, the findings remain robust across specifications, further supporting the central role of social capital. Additionally, trust in institutions reports a modest and marginally significant association with happiness across models, with estimates of β = 0.114* in Model 1 and β = 0.088* in Model 3, indicating a modest but positive effect of institutional trust on subjective happiness.

This general model did not offer further insights for interaction terms since both interactions – SC × MH and SC$_{high}$ × MH – were non-significant across models with *p–values* at 0.398 and 0.216, respectively. However, their coefficients remain positive, potentially indicating a protective role of social capital in reducing the impact of mental health on subjective happiness.

Finally, considering other predictors of subjective happiness, mental health and general health present the strongest effect on happiness across all models, while education level and financial well-being play a comparatively smaller role. Mental health arises as the strongest negative predictor of happiness in the general model (β = –0.789*** in Model 4) and general health has a robust effect with a β = 0.541***. Education level shows a negative impact (β = –0.142** in Model 2 and β = –0.184** in Model 4), while financial well-being positively affects happiness (β = 0.107** in Model 2; β = 0.135** in Model 4).

Table 1.4: Ordered Probit estimates for the weighted general model

	Model 1	Model 2	Model 3	Model 4
Social capital	0.395*** (0.071)	0.392*** (0.071)		
Social capital$_{high}$			0.414*** (0.124)	0.396*** (0.124)
Trust in institutions	0.114* (0.060)	0.113* (0.060)	0.088* (0.068)	0.083 (0.068)
SC × MH		0.027 (0.072)		
SC$_{high}$ × MH				0.166 (0.134)
Gender	0.055 (0.129)	0.054 (0.128)	0.103 (0.156)	0.094 (0.157)
Age	–0.068 (0.044)	–0.067 (0.044)	–0.142*** (0.054)	–0.140*** (0.054)
Ethnicity	0.018 (0.138)	0.020 (0.138)	0.076 (0.160)	0.079 (0.160)
Education level	–0.142** (0.061)	–0.142** (0.061)	–0.181*** (0.070)	–0.184*** (0.070)
Financial well-being	0.108** (0.052)	0.107** (0.052)	0.142** (0.060)	0.135** (0.061)
General health	0.548*** (0.074)	0.547*** (0.074)	0.539*** (0.085)	0.541*** (0.084)
Mental health	–0.659*** (0.071)	–0.660*** (0.071)	–0.704*** (0.081)	–0.789*** (0.106)
Observations	502	502	502	502
1|2	–0.639* (0.352)	–0.641* (0.352)	–0.617 (0.416)	–0.645 (0.417)
2|3	0.447 (0.351)	0.446 (0.351)	0.448 (0.416)	0.427 (0.417)
3|4	2.084*** (0.359)	2.083*** (0.359)	2.075*** (0.426)	2.058*** (0.427)

Notes: SC is for social capital; MH is for mental health.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Exact p-values available upon request.*

1.10.2 Results for mental health subsamples

Since the interaction terms between social capital and mental health did not provide significant evidence for a protective role of social capital against the effect of poor mental health, its role across different mental health severity levels (low, moderate, and high) and mental health profiles (SEM, MSM, and CAPS) was examined. In both cases, social capital shows a positive and significant effect at moderate and high levels of mental health severity, as well as among individuals with psychological (MSM) and psychiatric (CAPS) conditions. Using npCBGPS and PSM, the interaction coefficients remained stable even after model adjustments.

Table 1.5 presents the subsample analysis. Social capital has a positive and significant effect as mental health severity increases, acting as a moderating and protective factor in the relationship between mental health and happiness. In the case of moderate-severity mental health (MH_{mod}), social capital appears as a highly significant predictor (β = 0.491***). In the high-severity model (MH_{high}), the effect of social capital is comparatively lower but still highly significant β = 0.369***. Conversely, the low-severity mental health model (MH_{low}) does not provide evidence for a significant effect of social capital.

Table 1.5: Subsample Ordered Probit estimates with weighting balance

	MH_{low}	MH_{mod}	MH_{high}
Social capital	0.130	0.481***	0.379***
	(0.129)	(0.132)	(0.114)
Trust in institutions	–0.070	0.111	0.136
	(0.116)	(0.118)	(0.089)
Gender	0.107	0.278	–0.215
	(0.209)	(0.229)	(0.242)
Age	0.078	–0.068	–0.241***
	(0.078)	(0.082)	(0.074)
Ethnicity	0.105	–0.099	0.230
	(0.244)	(0.238)	(0.245)
Education	–0.034	–0.125	–0.231**
	(0.110)	(0.106)	(0.104)
Financial well-being	0.011	0.110	0.183**
	(0.093)	(0.089)	(0.092)
General health	0.550***	0.843***	0.615***
	(0.183)	(0.133)	(0.103)
Observations	167	167	167
1|2	0.049	–0.235	–0.369
	(0.835)	(0.594)	(0.533)
2|3	0.569	1.345**	0.628
	(0.819)	(0.599)	(0.537)
3|4	2.017**	3.315***	1.998***
	(0.828)	(0.631)	(0.548)

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Exact p-values available upon request.*

1.10.3 Results for mental health clusters

The cluster model with mental health profile (Table 1.6) supports the subsample analysis. Social capital is positively associated with happiness in both the MSM and CAPS groups, while only a marginally significant effect at the 10% level is observed in the SEM group ($\beta = 0.273$*). This weaker association suggests that, among SEM individuals, happiness may be shaped by a broader set of life domains beyond relational resources alone.

The effect is strongest in the MSM group, with a coefficient of $\beta = 0.699$*** for continuous social capital. In the CAPS group, which includes individuals with psychiatric conditions, the association remains strong ($\beta = 0.352$***) but comparatively lower than the MSM group, likely reflecting the presence of more complex clinical needs and constraints among psychiatric patients. In this group, trust in institutions emerges as an additional significant predictor of happiness ($\beta = 0.184$**).

Table 1.6: Cluster Ordered Probit estimates with weighting balance

	SEM	MSM	CAPS
Social capital	0.273*	0.699***	0.352***
	(0.144)	(0.150)	(0.109)
Mental health	–0.533***	–0.760***	–0.665***
	(0.154)	(0.155)	(0.126)
Trust in institutions	0.008	–0.052	0.184**
	(0.128)	(0.134)	(0.082)
Gender	0.106	0.324	0.011
	(0.219)	(0.306)	(0.205)
Age	0.062	–0.024	–0.170**
	(0.084)	(0.093)	(0.071)
Ethnicity	–0.285	0.084	0.141

	(0.324)	(0.266)	(0.211)
Education level	0.026 (0.107)	–0.298** (0.133)	–0.183* (0.098)
Financial well-being	0.025 (0.100)	0.201** (0.101)	0.107 (0.082)
General health	0.576*** (0.169)	0.293** (0.146)	0.767*** (0.109)
Observations	160	136	206
1|2	–0.622 (0.844)	–0.983 (0.717)	–0.541 (0.515)
2|3	0.818 (0.782)	–0.157 (0.711)	0.630 (0.521)
3|4	2.248*** (0.794)	1.688** (0.729)	2.496*** (0.536)

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Exact p-values available upon request.*

1.10.4 Results for covariates

Beyond social capital, several covariates indicate steady associations with happiness across the subsample and cluster models. General health emerges as a very strong and reliable predictor in all specifications. Financial well-being demonstrates a significant positive effect in the high-severity mental health group (β = 0.183**) and in the MSM group (β = 0.201**), highlighting its importance in the context of psychological vulnerability. Education is negatively related with happiness in the high-severity model (β = –0.231**), the MSM group (β = –0.298**), and the CAPS group (β = –0.183*). Age is significant only in the high-severity model (β = –0.241***) and CAPS group (β = –0.170**), indicating that older individuals with more severe mental health conditions tend to report lower levels of happiness.

1.11 Nonlinear effects

The weighted regression analyses confirmed a coherent relationship between social capital and subjective happiness across mental health profiles. To assess potential nonlinear effects, interacted quadratic OLS models – including linear and squared terms for social capital as well as their interactions with mental health indicators (e.g., continuous score, severity tertiles, and clinical clusters) – were estimated. The turning points of the fitted curves were calculated to examine the presence of concave or inverted U-shaped relationships, indicating whether the benefits of social capital saturate at certain levels of happiness. Visual representations are provided in this section, while full regression outputs are reported in the Appendix (Figure A.10, Figure A.11, Figure A.12).

In the general model (Figure 1.1), where mental health is treated as a continuous variable, social capital shows a significant positive association with happiness (β = 0.224, $p < 0.001$), while mental health is negatively associated (β = –0.387, $p < 0.001$). Although neither the linear interaction (SC·MH: β = 0.047, p = 0.240) nor the quadratic one (SC^2·MH: β = 0.002, p = 0.972) reaches statistical significance, predicted values illustrate a meaningful gradient: individuals with better mental health (few or no symptoms) reach peak happiness at a social capital level of approximately 1.97, compared to 2.79 (moderate symptoms), and 3.70 (severe symptoms). This suggests that those with more severe mental health symptoms require higher levels of social capital to experience maximum well-being, despite the lack of significant interaction effects.

In the subsample model (Figure 1.2), which categorizes mental health into tertiles, individuals with moderate (β = –0.254, p = 0.019) and high-severity (β = –0.689, p < 0.001) symptoms report significantly lower happiness compared to the low-severity group. Social capital remains positively linked with happiness (β = 0.147, p = 0.041), even if the interaction with higher mental health severity group was not statistically significant ($SC \cdot MH_{high}$: β = 0.090, p = 0.291). The turning points analysis reveals that predicted happiness peaks at a social capital level of 1.83 for the low-severity group, 0.99 for the moderate group, and 1.69 for the high group. This pattern points to diminishing returns at lower levels for individual with moderate symptoms, suggesting an inverted U-shaped relationship.

In the cluster model (Figure 1.3), based on clinical classifications, the main effect of social capital is not statistically significant (β = 0.090, p = 0.235). However, MSM individuals exhibit a significant positive interaction ($SC \cdot MSM$: β = 0.319, p = 0.005) and a marginally significant negative quadratic interaction ($SC^2 \cdot MSM$: β = –0.287, p = 0.073), indicating a concave curve. The predicted peak occurs at 0.63 for MSM, compared to 1.13 for SEM and 1.26 for CAPS. This points to the fact that MSM individuals experience more pronounced early gains in happiness from social capital but also reach a saturation point more quickly. Overall, while social capital remains positively associated with happiness, its marginal returns vary considerably across mental health groups. It appears more linear for SEM and CAPS, displaying a steady rise with greater social capital, and nonlinear for MSM individuals, who benefit more rapidly but reach their peak at lower levels of social capital.

Figure 1.1: Relationship between social capital and happiness in the general model

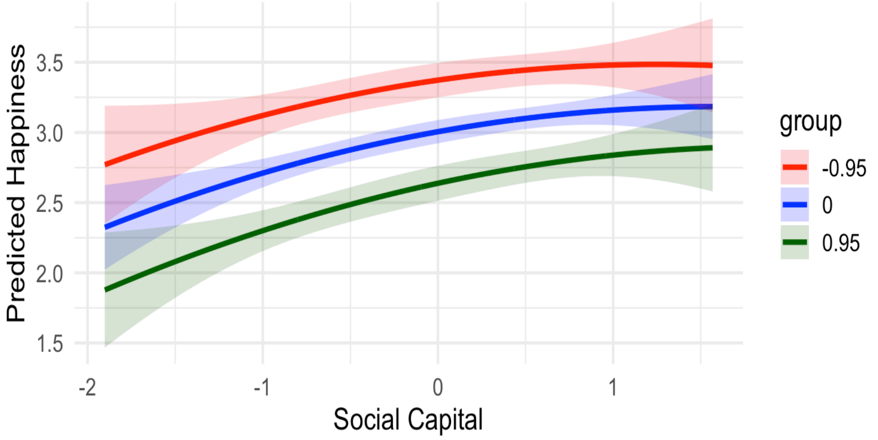


Figure 1.2: Relationship between social capital and happiness in the subsample model

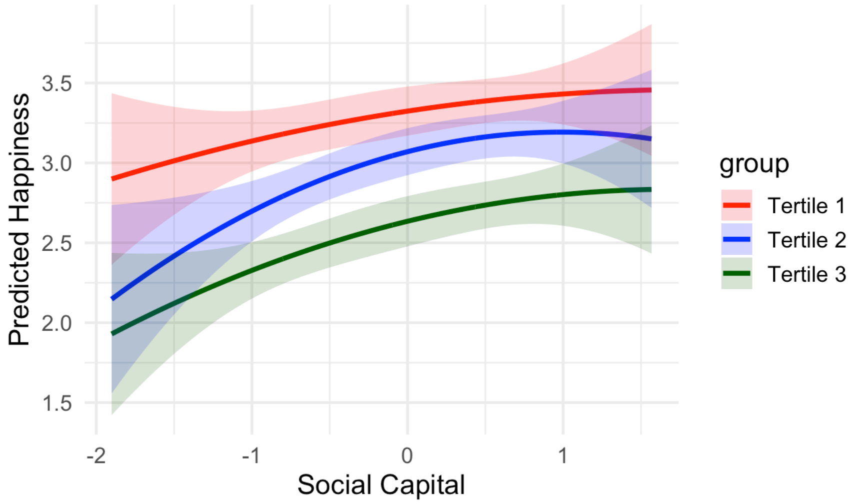
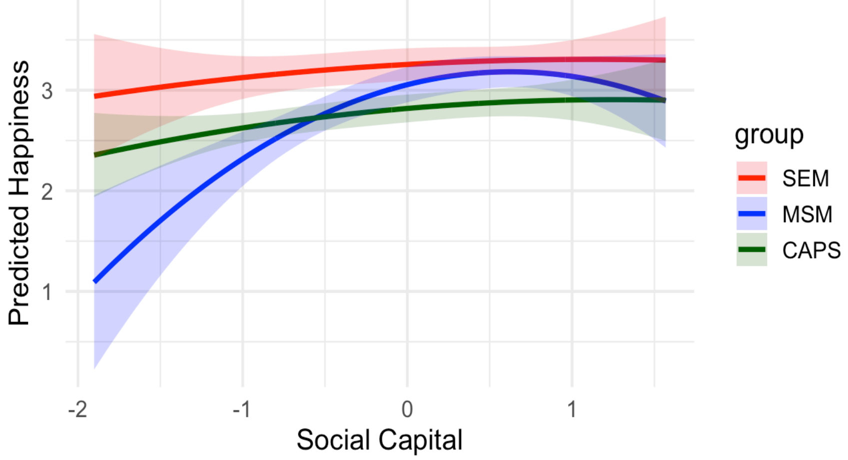


Figure 1.3: Relationship between social capital and happiness in the cluster model



1.11 Robustness checks and marginal effects

1.12.1 Bootstrapping

To assess the robustness of the estimated effects in the subsample and cluster models, a non-parametric bootstrap procedure was applied. Bootstrapping is a flexible and robust resampling technique widely applied in social science research (Carsey & Harden, 2014). It generates multiple samples with replacement from the original dataset, re-estimating the parameter of interest θ. This method enables the calculation of non-parametric confidence intervals without assuming a known population distribution. This process involves three key steps: (*i*) drawing a bootstrap sample S_{boot} of size n, where each observation has an equal probability of being selected $1/n$; (*ii*) calculating a new estimate $\hat{\theta}$ from this sample; and (*iii*) repeating the process J times to generate a vector V of bootstrap estimates of θ. This technique allows for the estimation of standard errors or confidence intervals based solely on the empirical distribution of the data. Independent resampling with replacement ensures that the resulting samples accurately capture the inherent variability of the original dataset.

In this study, 1,000 bootstrap samples were generated from the original dataset. For each sample, a linear regression model was estimated to derive the coefficient of social capital. The resulting distribution of estimates was then used to construct 95% non-parametric confidence intervals. This approach, free from parametric assumptions, provided a robust means to quantify statistical uncertainty and reinforced the reliability of the findings.

As shown in Table 1.7 and Table 1.8, the bootstrap distributions confirm the consistency of the social capital coefficient on subjective happiness across subsample and cluster models. In the subsample model, bootstrapped confidence intervals remain positive, confirming robustness across all levels of mental health severity: low-severity (*CI:* 0.028, 0.327), moderate-severity (*CI:* 0.103, 0.372), and high-severity (*CI:* 0.160, 0.471). In the cluster model, the results again present consistent and meaningful effects: SEM (*CI:* 0.005, 0.286), MSM (*CI:* 0.220, 0.573), and CAPS (*CI:* 0.081, 0.325). Further visual details are provided in the Appendix (Figure A.13).

These results reinforce the heterogeneity of effects across mental health groups and strengthen the empirical credibility of the findings. Across all specifications, social capital uniformly demonstrates a significant and positive association with subjective happiness. These results highlight the progressively stronger protective role of social capital on happiness as mental health severity increases, offering empirical support for its moderating role in high-vulnerability contexts. The relationship is strongest and most stable within the MSM group, followed by the CAPS group. Although the effect observed in the SEM group was comparatively weaker, it remains statistically significant.

Additionally, analysis of the bootstrap estimates from multiple regression models shows that institutional trust has no significant association with happiness, as its confidence intervals included zero across all specifications. Age is negatively related with happiness exclusively in the high-severity and CAPS groups, suggesting that older individuals with more severe mental health conditions experience lower well-being. Belonging to an ethnic group corresponds to lower happiness levels in the high-severity subsample and MSM group. Mental health consistently reports a strong negative effect across all groups. Self-reported general health, by contrast, exhibits a positive and significant association with happiness in the SEM and CAPS groups, further supporting the relevance of physical well-being for subjective life evaluations. Financial well-being emerges as a robust and significant predictor in most models, except in the MSM group, indicating that economic stability plays a more prominent role among individuals not engaged in psychological care.

Overall, these findings support the view that social capital plays a particularly vital role among individuals with higher mental health severity and those already engaged in mental health care.

Table 1.7: Bootstrap 95% confidence intervals from subsample model

	Low-severity		Moderate-severity		High-severity	
	2.5%	*97.5%*	*2.5%*	*97.5%*	*2.5%*	*97.5%*
Constant	0.91803557	2.51042755	1.23988024	2.31345776	1.98675382	3.92938141
Social capital	0.02840409	0.32741170	0.10303678	0.37166192	0.15961180	0.47149202
Trust in institutions	-0.12721657	0.11645957	-0.07948826	0.19344994	-0.01913300	0.23804474
Gender	-0.17873717	0.28536618	-0.07920032	0.36963647	-0.43374775	0.18230947
Age	-0.04448212	0.10482422	-0.10760103	0.04300216	-0.24877045	-0.04085037
Ethnicity	-0.18670559	0.34450184	-0.23759815	0.21147413	-0.16335124	0.50465134
Education	-0.11714666	0.09071446	-0.17995478	0.04676931	-0.30103717	-0.03298993
Financial well-being	-0.11978292	0.08814209	-0.02648315	0.15453354	0.01462483	0.25004113
General health	0.08457617	0.45060671	0.26816521	0.55414883	0.17072926	0.48570965
Mental health	-0.94591452	-0.38897994	-0.55674387	0.11664986	-1.05360226	-0.40705244

Table 1.8: Bootstrap 95% confidence intervals from cluster model

	SEM group		MSM group		CAPS group	
	2.5%	*97.5%*	*2.5%*	*97.5%*	*2.5%*	*97.5%*
Constant	1.560804363	3.04044150	1.549984285	3.394533792	1.2860750487	2.50724781
Social capital	0.005449675	0.28607999	0.220347848	0.573544539	0.0808473959	0.32496836
Trust in institutions	-0.118210673	0.13091480	-0.185761674	0.142201325	0.0001975111	0.21033696
Gender	-0.186360805	0.26716907	-0.193231826	0.512000976	-0.2387694441	0.22370550
Age	-0.054764545	0.09477102	-0.140244478	0.093104177	-0.1724852599	-0.01041290
Ethnicity	-0.290377568	0.16428469	-0.312885987	0.387024260	-0.0862242960	0.35537969
Education	-0.126397810	0.09249095	-0.302452946	-0.001430269	-0.1898837253	0.01583686
Financial well-being	-0.108543793	0.09113395	-0.012314966	0.217355577	-0.0293307675	0.15346245
General health	0.119536591	0.45586164	-0.003139787	0.345322087	0.3112780348	0.58294663
Mental health	-0.450975582	-0.10823100	-0.602263618	-0.282542236	-0.5219204191	-0.23040487

1.12.2 Testing nonlinearity using marginal effects

Table 1.9 summarizes the average marginal effects (AMEs) of social capital on subjective happiness across the three models.

In the general model, social capital reliably demonstrates a positive and statistically significant effect on happiness, with the strength of the association increasing among individuals with more severe mental health symptoms, in particular for those in the moderate (MHS_{mod}) and high (MHS_{high}) severity categories.

In the subsample analysis, this positive effect persists across all severity levels. However, it appears weaker and more variable among those with milder mental health symptoms (MH_{low}), suggesting potential variability in how social capital influences happiness in this group. The cluster model confirms this pattern: while no significant effect is detected for SEM, stronger and statistically significant effects are observed among MSM and CAPS individuals.

Overall, these findings support the presence of a nonlinear relationship, whereby the benefits of social capital on happiness increase among individuals with greater mental health needs. The particularly strong effect observed for the MSM group implies that social capital may serve as a buffer against psychological conditions, especially within clinically vulnerable populations.

Table 1.9: AMEs of social capital on happiness across general, subsample, and cluster models

Factor	*AME*	*SE*	*z*	*p-value*	*Lower*	*Upper*
MHS_{low}	0.1774	0.0582	3.0509	0.0023	0.0635	0.2914
MHS_{mod}	0.2245	0.0404	5.5535	0.0000	0.1452	0.3037
MHS_{high}	0.2715	0.0554	4.8972	0.0000	0.1628	0.3801
MH_{low}	0.1472	0.0707	2.0820	0.0373	0.0086	0.2857
MH_{mod}	0.2475	0.0724	3.4163	0.0006	0.1055	0.3895
MH_{high}	0.2371	0.0682	3.4750	0.0005	0.1034	0.3708
SEM	0.0903	0.0761	1.1868	0.2353	-0.0588	0.2394
MSM	0.4097	0.0861	4.7566	0.0000	0.2409	0.5786
CAPS	0.1388	0.0668	2.0786	0.0377	0.0079	0.2697

The general model (MHS_{low}, MHS_{mod}, MHS_{high}) uses interaction terms within the full sample, while the subsample model (MH_{low}, MH_{mod}, MH_{high}) estimates separate regressions for each mental health severity group. The cluster model refers to clinically derived categories: SEM, MSM, and CAPS.

1.13 Discussion

The association between social capital and subjective happiness has been widely documented in the literature (Rodríguez-Pose & von Berlepsch, 2014; Pancheva & Vásquez, 2022; Bartolini *et al.*, 2023). This study reinforces those findings, identifying social capital – measured through indicators such as friendships, social meetings, social participation, volunteering, and sense of social inclusion – as a determinant of happiness and well-being, even when controlling for socioeconomic and health-related factors. Unlike much of the existing research, which typically focuses on general populations or high-income settings, this investigation centers on a developing context: the peripheral neighborhoods of Fortaleza, Ceará, Brazil. These districts are characterized by high levels of marginalization, economic instability, limited public service provision, and elevated exposure to violence.

Within these vulnerable settings, individuals living with mental health conditions – ranging from psychological distress to clinically diagnosed psychiatric conditions – are especially at risk. Previous studies have shown that people facing mental health conditions are among the most socially excluded and stigmatized groups (Rössler, 2016; Hall *et al.*, 2019), particularly in environments where their condition poses a barrier to employment, education, and social participation in community life.

Following the structure of the study, the discussion below presents the main findings in alignment with the proposed research hypotheses.

H-1: Individuals with higher levels of social capital report significantly greater subjective happiness compared to those with lower levels.

Overall, social capital is strongly and positively connected with subjective happiness. These results are coherent with previous findings demonstrating that robust social networks, social ties, sense of belonging, and active social engagement contribute significantly to happiness (Gómez-Balcácer *et al.*, 2023). In this context, social capital functions as a non-material asset – including emotional, relational, and social resources – that can meaningfully enhance individual well-being. The findings suggest that individuals with higher levels of social engagement tend to experience higher reported levels of happiness, reinforcing the idea that social connectedness offers both emotional and psychological resources critical for navigating adversity.

H-2: Social capital moderates the negative effects of mental health conditions on happiness; even in presence of such conditions, individuals with higher social capital are expected to report higher happiness.

Social capital is widely recognized as a key determinant of mental health and well-being, with numerous studies linking its psychosocial and network components to improved outcomes (Bassett & Moore, 2013). Among these, social ties and perceived social support have appeared as predictors of mental health, although their impact may vary across different population groups (Kawachi & Berkman, 2001). In line with this literature, our findings indicate that social capital significantly predicts higher levels of happiness among individual with mental health conditions. This supports the hypothesis that social capital plays a dual role, in promoting positive affective states and buffering the detrimental effects of poor mental health. The evidence aligns with the mediating pathway proposed by Fei *et al.* (2023), where social capital indirectly enhances subjective well-being through improvements in physical and mental health.

The protective effect of social capital becomes more prominent as the severity of mental health conditions increases. Among individuals with moderate (MH_{mod}) and high (MH_{high}) mental health severity, its impact on happiness differs. The buffering effect weakens in the highest-severity group (from 0.481*** to 0.379***), suggesting a possible threshold effect. The nonlinearity test of the relationship between social capital and happiness across levels of mental health severity showed that, in the general model, the turning points of predicted happiness vary meaningfully with mental health severity, proposing that individuals with more severe symptoms may require disproportionately higher levels of social capital to attain comparable levels of happiness. Similarly, in the subsample model, the lower turning point among individuals with *moderate* symptoms (0.99) compared to those with *high* (1.69) and *low* (1.83) symptom severity, supports the idea of diminishing marginal returns, especially at moderate levels of distress, and is consistent with an inverted U-shaped relationship. This may indicate that beyond a certain level of severity of mental health symptoms – such as major depression, chronic anxiety, or acute psychological distress – social capital alone may be insufficient to maintain subjective happiness. These results point to the limits of informal support systems in shaping well-being, likely due to the overwhelming burden of clinical conditions.

This role of social capital is supported by prior findings. Bertotti *et al.* (2013) studied the protective effect of social networks against common mental disorders, in contrast to the potential risk posed by civic participation. Laurence & Kim (2021) also found that individual level social capital is associated with reduced psychological distress, while Park *et al.* (2023) demonstrated that a positive sense of community correlates lower odds of reporting depression, anxiety, and stress. Moreover, Biddle *et al.* (2025) – studying refugee migrants with experiences of discrimination – observed that levels of community trust seem to buffer the negative mental health impacts for refugees.

In low-resource contexts, such as the peripheral neighborhoods of Fortaleza where access to formal mental health care is often limited, social capital may become a therapeutic resource, offering emotional and psychological support. While it cannot replace medical or proper therapeutic treatments, it functions as a resilience mechanism, especially for individuals facing moderate mental health conditions such as psychological distress. Therefore, integrating social capital strategies as complementary interventions within mental health policies and clinical frameworks can help improve overall well-being.

H-3: The effect of social capital on happiness varies across mental health treatment groups. The strongest positive effects are expected among MSM and CAPS participants, whereas the influence is weaker among SEM individuals, who are not engaged in any form of mental health treatment.

The effect of social capital differs significantly across clinical mental health clusters, indicating that psychological vulnerability shapes how individuals benefit from social resources. The regression estimates confirm that individuals in the MSM group, who receive psychological treatment, experience the strongest impact of social capital, followed by those in the CAPS group, while in the SEM group, which represents individual not engaged in any form of mental health treatment, reveals the weakest effect.

This gradient reinforces the interpretation that social capital becomes increasingly important as mental health severity intensifies, especially in contexts of psychological distress and psychiatric conditions where social capital may offer emotional regulation, belonging, and access to informal coping strategies (Kawachi & Berkman, 2001; Laurence & Kim, 2021).

However, the effect among MSM patients is not only strong but also nonlinear. The concave trend, reflected in the interaction and quadratic models, indicates that while this group benefits rapidly from social capital, the gains peak at relatively low levels of social engagement (around 0.63), indicating early saturation. This aligns with the inverted U-shaped relationship observed in moderate-severity subsample models (*H-2*) and reinforces the idea that individuals facing psychological challenges may be more responsive to social engagement up to a point, after which the marginal benefits decline. Nonetheless, the marginal returns suggest that, for MSM patients, increased social involvement initially provides validation, emotional support, and a sense of belonging. Yet, when social demands exceed or fail to meet their emotional needs, this can result in tiredness, unmet expectations, or even forms of self-isolation.

This threshold pattern is less evident among CAPS patients, likely due to the greater functional impairment and reduced social engagement commonly associated with chronic psychiatric conditions and comorbidities. As the marginal returns show, individuals in the CAPS group may experience a more persistent and profound disconnection from social life. For them, the reduced marginal benefits may reflect long-standing unmet needs. While a positive effect of social capital remains, its magnitude appears weaker, likely because the strength of this association depends on the specific type of social capital considered and the class of mental disorder (Hirota *et al.*, 2022).

Overall, the findings from *H-2* and *H-3* converge on a key insight: the role of social capital in shaping happiness is conditional and non-linear, with its utility varying across mental health profiles. Social capital functions most effectively as a buffer and enhancer of well-being for individuals with moderate to high psychological vulnerability, though its returns are not limitless, highlighting the need to pair community-based engagement with adequate clinical and therapeutic support.

Finally, institutional trust emerges as marginally significant determinant of subjective happiness, particularly among individuals experiencing the most severe mental health conditions (CAPS). These findings are consistent with prior studies, which emphasize the importance of institutional trust in supporting well-being, especially in contexts where individuals rely on public services for mental health care (Bachmann *et al.*, 2023; Alegría *et al.*, 2018). For individuals with psychiatric conditions, trust in governmental and healthcare institutions may offer a sense of stability, safety, and security, thereby contributing positively to their overall well-being.

1.14 Conclusion

This study is the first to investigate the relationship between social capital and subjective happiness across different mental health profiles in the peripheral neighborhoods of Fortaleza, Ceará, Brazil – a highly vulnerable and under-researched context. Data were collected through a standardized questionnaire administered in person by the researcher. The support of the Movimento de Saúde Mental helped to ensure consistency and foster trust in a context often characterized by skepticism toward outsiders.

By combining OLS regression with nonparametric balancing techniques (PSM and npCBGPS), the analysis improves causal interpretation and provides robust estimates, supported by bootstrap confidence intervals.

Findings confirm the central role of social capital – expressed through friendships, social participation, social interactions, volunteering, and perceived inclusion – as a non-material determinant of happiness and well-being, highlighting its therapeutic relevance beyond economic and health-related conditions. Interestingly, this positive association persists even after controlling for mental health status and type of treatment – whether psychological or psychiatric – supporting a therapeutic and protective function of social capital.

However, the impact of social capital is not uniform. Non-linear and conditional relationship indicate that individuals with moderate or higher vulnerability benefit most from social capital, but the marginal gains tend to diminish beyond a certain threshold. Among those with more severe symptoms, higher levels of social capital are needed to reach comparable levels of happiness. Specifically, individual receiving psychological care (MSM group) report strong benefits from social capital, but the gains tend to level off early, possibly because social involvement may no longer provide additional emotional support. In contrast, those with psychiatric diagnoses (CAPS group) experience weaker effects, likely due to long-standing impairment that reduces capacity for social participation.

In sum, social capital emerges as a critical but not unlimited resource for enhancing subjective happiness, especially in contexts marked by structural adversity such as poverty, marginalization, and limited access to care. In such settings, its impact is most effective when integrated with accessible public health strategies and human-centered mental health support.

1.15 Policy implications

The findings of this study stress the need to integrate social capital into public mental health policies as a therapeutic and preventive resource. Given its stronger impact among individuals with moderate to severe mental health conditions, social capital should be actively included not only in community-based programs but also as a complementary dimension within specialized psychological and psychiatric care. Even for individuals without a clinical diagnosis, social engagement and inclusion may serve as protective factors that promote subjective well-being.

In peripheral and fragile urban contexts such as vulnerable neighborhoods of Fortaleza, a dual-track approach, combining clinical care with social support mechanisms, could offer more comprehensive and effective responses to mental health disparities. This requires reinforcing relational networks among peers and within the community, facilitating participation in collective and solidarity activities, valorizing individual competences and capabilities, and promoting inclusive practices to combat stigma and social isolation.

From a public health perspective (WHO, 2022a), investment plays a central role. Expanding access to decentralized health facilities, supporting grassroots organizations, and fostering cooperation between state and civil society actors are essential for building sustainable mental health ecosystems. Policies should prioritize bottom-up redistribution and recognize the social value of marginalized groups, moving beyond model based on isolation and stigma. A more equitable allocation of resources and more person-centered outcomes can be achieved by tailoring interventions to distinct vulnerabilities and care pathways: preventive strategies for SEM individuals, integrative psychosocial support for MSM, and multidisciplinary care for CAPS.

This framework is already being implemented in practice in the case Grande Bom Jardim. Here, the collaboration between CAPS Geral V and Movimento de Saúde Mental offers an innovative model of integrated care. While CAPS provides clinical and psychiatric services, the Movimento complements them by implementing PICS (*Práticas Integrativas e Complementares em Saúde* – Integrative and Complementary Practices for Health), which represent a form of community-based psychosocial intervention. Their joint initiative led to the creation of the *CAPS Comunitário of Bom Jardim* (Community CAPS of Bom Jardim), a local facility representing a reference point for the entire community. This initiative is grounded in the *Abordagem Sistêmica Comunitaria* (Systematic Community Approach), a model that promotes preventive relief and social therapy for individuals experiencing mental distress as well as those without specific diagnoses. Its broader scope is to promote mental health and social inclusion for all in fragile contexts such as peripheral urban areas.

This experience may become a replicable model for similar communities across the Global South, where public health systems often remain underfunded and fragmented (Patel *et al.*, 2018), making community-based responses essential.

1.16 Limitations

This study has several limitations that should be acknowledged. First, despite the use of balancing technique such as Propensity Score Matching and Nonparametric Covariate Balancing Propensity Score, the observational design prevents us from establishing definite causal relationships. The absence of valid instrumental variables and the potential influence of unobserved confounders may affect the robustness of the findings.

Second, the sample size is relatively limited (n = 502), and the population is not representative of the entire mental health population or all residents of Grande Bom Jardim. The data reflect specific contextual conditions that may limit generalizability.

Third, the gender imbalance observed – particularly, the higher number of female participants – may reflect broader structural and cultural factors. These include men's lower propensity to seek mental health care (Liddon *et al.*, 2017), women's greater availability for survey participation due to unpaid care roles (UNWOMEN, 2019), and the presence of men in informal or illicit activities in Brazilian favelas (Rodgers & Baird, 2015), which can limit their visibility and accessibility during fieldwork.

Despite these limitations, the study offers valuable insights into the interaction between social capital, mental health, and happiness in a highly underexplored urban context.

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Chapter 2

2. Can subjective happiness protect against crack/cocaine use and injection drug use? An instrumental variable study of the U.S. population

Abstract

Substance use is a persistent global issue with serious public health and social consequences. In the U.S., it is shaped by a complex interplay of individual, familial, and social factors. This study examines the causal effect of subjective happiness on substance use, focusing on crack/cocaine consumption and drug injection. Using nationally representative data from the General Social Survey and an instrumental variable approach (2SRI) to address potential endogeneity, the analysis shows that higher levels of happiness significantly reduce the likelihood of crack/cocaine use (β = –0.353, p < 0.046) and drug injection (β = –0.459, p < 0.018), controlling for demographics, socioeconomic background, stressful life events, and adverse experiences during adolescence. Additional exploratory results indicate the importance of early-life conditions, such as family structure and living environment, in shaping later vulnerability to substance use. These findings clarify the direction of the causal relationship between happiness and substance use, lending strong support to the *social causation hypothesis*. They suggest that subjective happiness functions as a protective factor against severe forms of addiction. Public health strategies should therefore prioritize well-being, social capital, and collective resilience, complementing traditional approaches that focus mainly on punitive measures or individual responsibility.

2.1 Introduction

Substance use is a persistent global issue with serious implications for public health and social well-being. It is a multifaceted behavior shaped by a complex interplay of individual, familial, community, and structural factors (UNODC, 2015). People use substances for various reasons, including pleasure, relaxation, increased self-confidence, or as a coping mechanism for stress and psychological distress (NIDA, 2020; WHO, 2024). While often starting voluntarily, substance use can evolve into dependence due to its neurological effects, particularly through the dopamine system (Barrett & Simmons, 2015). This creates a cycle where substance use takes precedence over relationships, health, and employment, further reinforcing its role as a maladaptive coping tool (Miller *et al.*, 2022).

Understanding substance use requires a comprehensive examination of both endogenous and exogenous vulnerabilities. Biological sex (Becker *et al.*, 2017; McHugh *et al.*, 2018), genetic predispositions (Volkow & Li, 2005), personality traits (Zilberman *et al.*, 2018), and mental health conditions (Goldstein *et al.*, 2009) are key individual factors. Childhood trauma, academic failures, psychological stress during adolescence, peer pressure, and increased access to substances further heighten the risk (UNODC, 2015; NIDA, 2020; CDC, 2024). Family history of substance abuse, low income, family instability, and identity-based rejection are also significant (Burlew *et al.*, 2009; CDC, 2024).

At the community and structural levels, weak social ties, exposure to violence, and limited access to healthcare and social protection might intensify vulnerability to substance use (UNODC, 2017; Amaro *et al.*, 2021; Reboussin *et al.*, 2020). Cultural and social stigma, punitive drug policies, and events like disasters, conflicts, or displacement further contribute the risk (Earnshaw, 2021). These dynamics highlight that substance use is not only a behavioral issue, but also a public health challenge shaped by wider social determinants.

This study aims to explore subjective happiness as a factor influencing substance use among the U.S. population. Subjective happiness is conceived here as living a meaningful life aligned with internalized values, consistent with the *eudaimonic perspective* of happiness and well-being. The study examines the impact of subjective happiness on substance use behaviors – specifically, crack/cocaine use and injection drug use – within a broad general population sample. Drawing on data from the General Social Survey (GSS), the analysis employs ordered regression models with a comprehensive set of controls, including demographics, socioeconomic status, and stressful life events.

To strengthen causal claims, the study adopts an instrumental variable approach through the Control Function method (2SRI). By isolating the direct impact of subjective happiness on substance use, this method addresses potential endogeneity arising from reverse causality and the bidirectional relationship between happiness and substance use, enhancing robustness and credibility.

The findings are expected to inform public health policies by emphasizing subjective happiness and well-being as protective factors against substance use, particularly in context where social capital is weak or underdeveloped. Policies that promote emotional well-being, resilience, and social inclusion – especially during adolescence – may reduce the risk, calling for a shift away from punitive models toward integrated and human-centered approaches across schools, communities, and institutions.

In this study, the term *substance use* refers to the consumption of psychoactive substances, both legal (e.g., alcohol, tobacco, prescription drugs when misused) and illegal (e.g., cocaine, crack, heroin). This terminology is preferred over “drug use” or “illicit drug use” to ensure conceptual precision and to avoid the stigma tied to legal classifications.

This chapter is structured as follows. Section 1 reviews the literature on subjective well-being and substance use. Section 2 describes socio-demographic patterns of crack/cocaine use and drug injection in the U.S. Section 3 outlines the main variables, while Section 4 presents the research question and the hypotheses. Section 5 introduces the empirical model and the IV strategy. Section 6 reports preliminary results, Section 7 details the instrumental variables analysis, and Section 8 presents the final findings. The chapter concludes with a discussion of policy implications.

The analysis was conducted using RStudio and Stata.

2.2 Theoretical background and literature review

This section presents the conceptual foundations and empirical findings on happiness and its relationship with substance use. By integrating psychological and economic theories, it compares hedonic and eudaimonic views of well-being, explores the role of intrinsic and extrinsic motivations, and examines the phenomenon of hedonic adaptation. The latter part focuses on the complex interplay between life satisfaction and substance use, with attention to the developmental, social, and motivational factors influencing this bidirectional relationship.

2.2.1 The eudaimonic concept of happiness

Happiness is a concept that varies across individuals, cultures, and life stages (Oishi *et al.*, 2013). Academic literature commonly distinguishes between two contrasting perspectives on happiness: the *hedonic* and *eudaimonic* views, each reflecting different interpretations of human nature. The *hedonic perspective* – rooted in Jeremy Bentham's philosophy – emphasizes the pursuit of pleasure and the avoidance of pain as fundamental motivators for human behavior (Moore, 2019). This view faces two major critiques. From an *environmental viewpoint*, hedonism is criticized for fostering over-consumption, societal decline, and resource depletion. From an *individual viewpoint*, it is argued that excessive indulgence in pleasures – such as drinking, smoking, unhealthy eating, frequent sexual activity, or substance use – can undermine personal health and well-being (Veenhoven, 2003). Furthermore, the hedonic perspective equates happiness with short-term experiences of pleasure, satisfaction, and gratification which are fleeting and fail to support lasting well-being (Lee & Carey, 2013). Once these fleeting pleasures fade, individuals may experience renewed feelings of dissatisfaction or unhappiness (Veenhoven, 2003).

Supporting this idea, Easterlin (2004; Easterlin & Switek, 2014) applied *Set-Point Theory* to explain why wealth or major life changes affect happiness only temporary. Because happiness is strongly shaped by genetics and personality, people tend to return to a stable baseline of well-being over time. This "hedonic adaptation" explains why levels of happiness stabilize after events such as marriage, job loss, lottery wins, or illness (Anusic *et al.*, 2014; Ormel *et al.*, 2017). The *Easterlin Paradox*, (Easterlin, 1974; Easterlin & O'Connor, 2020) further shows that while financial gains can briefly boost happiness, adaptation and social comparison prevent lasting improvements. These findings align with critiques of materialism, which emphasize that prioritizing extrinsic goal – wealth, success, consumption – over intrinsic ones like friendship, solidarity, and trust fosters dissatisfaction. Materialistic individuals tend to report lower happiness, self-esteem, and life satisfaction, and are more vulnerable to mental health conditions and substance use (Layard, 2005; Bartolini, 2011).

In contrast, the *eudaimonic perspective* of happiness is rooted in Aristotle's concept of *eudaimonia*, which conceptualizes that true happiness can be achieved by living fully actualized in alignment with virtues and personal values (Ryan *et al.*, 2008; Crespo & Mesurado, 2015). From this viewpoint, subjective well-being is not a fleeting emotional state but rather an ongoing process of realizing personal potential and fulfilling a meaningful life purpose (Deci & Ryan, 2008). Eudaimonia is typically associated with leading a balanced and harmonious daily life, fostering meaningful social relationships, attaining high life satisfaction (Myers & Diener, 1995; Carr, 2004), and experiencing a deep sense of purpose and meaningful existence (Lyubomirsky, 2007). This eudaimonic form of well-being emphasizes purposeful living, where personal development and alignment with deeply held values foster lasting satisfaction (Lee & Carey, 2013).

Therefore, psychological hedonism alone cannot fully account for the complexity of happiness (Ryan *et al.*, 2008; Frey, 2018). A more complete understanding requires incorporating the principles of eudaimonic well-being, as outlined in Self-Determination Theory (SDT) (Deci & Ryan, 2012). SDT implies that true happiness arises from fulfilling three fundamental psychological needs: *autonomy*, which refers to the ability to make self-directed choices; *competence*, a sense of mastery and effectiveness; and *relatedness*, the formation of meaningful and supportive relationships. When these intrinsic needs are fulfilled, individuals experience deeper well-being and lasting happiness through self-actualization and the pursuit of meaningful life goals.

Outside of treatment settings, studies show that individuals with *low autonomous motivation* and *higher controlled motivation* – i.e., behaviors driven by external pressures – are more prone to risky substance use, especially alcohol use. This vulnerability is often linked to a lack of self-confidence or perceived control, which compromises personal ability to self-regulate. In clinical contexts, interventions that support autonomy and competence – such as autonomy-supportive environments and training in self-regulation – have been found to improve recovery outcomes. However, the need for relatedness is frequently overlooked, likely because it relies on social support systems that extend beyond the therapeutic settings. Overall, SDT emphasizes how unmet psychological needs can lead individuals to use substances as a coping mechanism. Addressing these needs through supportive, motivation-based approaches can significantly reduce substance use and improve recovery prospects (Herchenroeder *et al.*, 2024).

2.2.2 Subjective happiness and substance use

The relationship between happiness and substance use has been interpreted in various ways. Existing literature presents two primary perspectives on this relationship, often framed within two bidirectional streams of thought. The first perspective focuses on the impact on how drug addiction negatively impacts on personal life, in terms of deterioration of life circumstances such as job loss, broken social connections, or legal issues. This view aligns with the *social selection hypothesis* which theorizes that drug addiction causes lower happiness and reduced overall life satisfaction (Hudson, 2005; Schmengler *et al.*, 2022). Conversely, second perspective suggests that social factors – such as poverty, harmful environments, unemployment, or other stressors – may increase the likelihood of substance use. This view aligns with the *social causation hypothesis*, which posits that low levels of happiness may lead individuals to engage in substance use behaviors (Dohrenwend *et al.*, 1992; Linton *et al.*, 2017).

In general, the literature indicates that the influence of substance use on happiness is largely negative. The World Happiness Report 2019 highlights this trend through Professor Jeffrey Sachs's analysis of growing addiction epidemic in the United States (Sachs, 2019). This includes not only substance abuse, but also behavioral addictions such as gambling, compulsive use of social media, video gaming, shopping, and consumption of unhealthy food. According to Sachs, these addictions contribute to substantial economic costs, increased personal unhappiness, rising depression rates, and broader social marginalization. The author presents three possible explanations for rising addiction rates. Firstly, modern lifestyles significatively diverge from our evolutionary heritage. Secondly, income inequality in high-income societies induces stress fueling addiction (Wilkinson & Pickett, 2019). Thirdly, market economies are designed to promote addictive products (e.g., slot machines, excessive screen time on smartphones, and highly processed food), exacerbating addictive behaviors. Taken together, these explanations illustrate how modern social and economic dynamics contribute to the spread of addictive behaviors and consequently the erosion of individual well-being.

Within this broader context, adolescence emerges as a particularly vulnerable stage of life, marked by increased susceptibility to peer pressure, a strong desire for novel experiences, and a higher likelihood of experimenting with substances. Clifford *et al.* (1991) found a curvilinear relationship between life satisfaction and drug use among college students: while complete abstinence may prevent drug use, moderate drug use – often related to social activities – can enhance life satisfaction, whereas chronic misuse of substances such as alcohol or cocaine tends to reduce it. Further studies support these findings. Sumnall *et al.* (2010) noted that younger substance users often prioritize fun and enjoyment over health concerns. Similarly, Zullig *et al.* (2001) reported that first-time marijuana or cocaine use is significantly associated with lower life satisfaction in individuals aged 13 or younger. Kang (2023), in a national longitudinal study in the UK, found that illegal drug use negatively correlates with life satisfaction among adolescents and young adults aged 16 to 22.

The literature detects a bidirectional relationship between happiness and substance use: on the one hand, substance use tends to erode happiness and life satisfaction, while on the other, higher levels of happiness appear to protect against the initiation and escalation of substance use.

A broad body of evidence indicates that substance use undermines life satisfaction, quality of life, and happiness across different substances. Bogart *et al.* (2007) discovered that early hard drug use at age 18 predicts lower life satisfaction at age 29, with continued use in adulthood explaining more than half of this decline. Similar findings emerge for opioid users, who reported markedly higher dissatisfaction compared to the general population (Luty & Arokiadass, 2008). Crack and cocaine consumption is particularly detrimental, impairing not only physical health but also social functioning, education attainment, and even religious involvement (Narvaez *et al.*, 2015). Chemical dependence also extends its negative effects to family members, generating psychological distress and worsening well-being (Moreira *et al.*, 2013). Cannabis presents a distinct pattern: Maccagnan *et al.* (2020) documented a sharper reduction in life satisfaction among cannabis users compared to users of other substances, while Sumnall *et al.* (2010) observed that early ecstasy use has similar long-term consequences. Nonetheless, some forms of treatment can partly offset this decline, as shown by Muller *et al.* (2016), who found that methadone or buprenorphine improve quality of life among individuals with opioid dependence. Insights from neuroscience further explain these dynamics: while substances initially stimulate hedonic systems, the incentive salience mechanism sustains craving even when subjective pleasure diminishes (Kringelbach & Berridge, 2010). Relatedly, Amigó (2023) reported that even mentally simulating cocaine's euphoric effects produces a temporary increase in happiness among former users.

At the same time, research points to the opposite direction: higher happiness levels appear to reduce the likelihood of substance use. Individuals who have never consumed psychotropic substances generally report greater life satisfaction than users. Early studies already suggested that unhappiness in adolescence increases vulnerability to later drug use (Bachman, 1979; Veenhoven, 2003). More recent evidence confirms this protective role of happiness: positive school environments and student well-being significantly lower the risk of drug addiction, predicting up to a 16% decrease in the likelihood of use (Nasrabadi *et al.*, 2013). Lew *et al.* (2018) similarly observed that adolescents with lower life satisfaction are more likely to consume tobacco, alcohol, and marijuana, often engaging in multiple substance use simultaneously. Longitudinal studies reinforce this pattern, demonstrating that declines in life satisfaction frequently precede the onset of addictive behaviors (Moschion & Powdthavee, 2017). Coherent results also emerge from Mahadzirah *et al.* (2018), who identified a significant negative link between life satisfaction and substance abuse, with delinquency acting as a mediator.

In conclusion, also personality traits and health behaviors significantly influence life satisfaction and are key factors in preventing substance addiction (Konaszewski & Muszyńska, 2019). A permissive attitude toward drug use is another strong predictor of substance use. Csabonyi & Phillips (2020) found that a strong sense of life purpose can protect young adults from substance use, with boredom acting as a mediating factor. Cheung *et al.* (2016) found that greater life satisfaction correlates with less permissive attitudes toward both occasional and regular drug use, while lower life satisfaction increases the likelihood of recent drug use. Furthermore, improving the quality of life for individuals in addiction recovery has been shown to enhance happiness and reduce relapse risk (Razali *et al.*, 2015; Khalid *et al.*, 2024).

2.3 Substance use in the U.S.

The phenomenon of substance use is a major public health public concern in the United States and globally. In 2022, more than 27 million people in the U.S. used illicit substances or misused prescription medications, reflecting an epidemic with significant social and economic consequences (HHS, 2023). Drug abuse contributes to a wide range of societal problems, including domestic and public violence, criminal behavior, and suicide (Miech *et al.*, 2023).

Since the 1960s, the U.S. has seen a steady rise in illicit drugs, leading to severe health outcomes such as increased morbidity (i.e., AIDS) and mortality (i.e., overdose deaths). Epidemiological studies revealed that in 1960, less than 5% of the population had used illicit drugs. This figure doubled to over 10% by the early 1970s and surged to an estimated 37.1% (75.4 million people aged 12 and older) by 1991. Drug use trends have also varied by substance. Marijuana use began rising in 1972 and peaked in 1979, while cocaine use increased during the 1970s, peaking in 1985 before declining until 1991 (Gfroerer & Brodsky, 1992). The economic burden of substance use was substantial, with the National Institute on Drug Abuse (NIDA) estimated costs of $98 billion in 1992. This included $14.6 billion in premature deaths, $9.9 billion in health care expenditure, and $14.2 billion in drug-related morbidity as detailed by Degenhardt *et al.* (2004) in the WHO's Comparative Quantification of Health Risks.

2.3.1 Current substance use and overdose trends

Over the past two decades, the United States has faced a stee rise in overdose deaths linked to prescription painkillers and heroin (Carpenter *et al.*, 2017). The age-adjusted rate of drug overdose deaths increased sharply, from 6.8 per 100.000 in 2001 to 32.4 per 100,000 in 2021, with men experiencing higher rates than women. Deaths involving natural and semi-synthetic opioids such as oxycodone and hydrocodone rose from 1.2 in 2001 to 3.5 in 2010, remaining stable thereafter. In contrast, psychostimulant-related deaths surged more recently, with the 2021 rate 33% higher than in 2020 (Spencer *et al.*, 2022). Geographically differences also persist. In urban counties, the age-adjusted drug overdose death rate climbed from 6.4 per 100,000 in 1999 to 22.0 in 2019, while in rural counties it rose from 4.0 to 19.6 (Hadegaard & Spencer, 2021).

Trends in treatment participation have also shifted. Between 2011 to 2020, the number of individuals in treatment for alcohol, drug, or combined use peaked at 1,356,015 in 2017 before declining to 1,224,127 in 2020 (SAMHSA, 2021). During this period, treatment for drug and alcohol use fell from 44 to 31%, and treatment for alcohol alone declined from 18 to 13%. By contrast, treatment for drug use alone rose markedly, from 38% to 52%**.**

The broader health and economic burden remain immense. According to the Institute for Health Metrics and Evaluation (IHME), drug use in the U.S. accounts for 1,703.3 disability-adjusted life years (DALYs) per 100,000 people – the second-highest rate worldwide. The country also ranks first in DALYs from cocaine use, third for opioid addiction, and second for amphetamines (Sachs, 2019). Financially, the estimated annual cost of substance use is $193 billion (HHS, 2023).

2.3.2 Drug classification and drug trends

The U.S. Drug Enforcement Administration (DEA) classifies drugs into five schedules based their accepted medical use and potential for abuse or dependency. Schedule I substances, such as heroin, ecstasy (MDMA), LSD, peyote, and marijuana, have no accepted medical use and a high potential for abuse. Schedule II includes drugs with recognized medical applications but a similarly high risk of abuse and severe dependence, such as cocaine, methamphetamine, methadone, oxycodone, and fentanyl. Schedule III-V substances are considered progressively less prone to abuse and dependence (DEA, 2024).

Patterns of drug use also vary considerably by age. For instance, around 7% of 18-year-olds report using marijuana compared to just 2% of 50-year-olds, while 8% of 18-year-olds and 5% of 50-year-olds report using other substances (Sachs, 2019). Among these, cocaine, heroin, methamphetamine, and fentanyl stand out as the most commonly used and among the most addictive, each carrying unique health and social consequences.

Cocaine, a highly addictive stimulant derived from the coca plant, can be snorted, smoked, injected, or rubbed onto the gums. In 2021, an estimated 4.8 million people aged 12 or older used cocaine, including nearly 1 million who used crack/cocaine. About 1.4 million individuals were diagnosed with a cocaine use disorder, and close to half a million initiated cocaine use that year most between 18 and 25 (SAMHSA, 2022). Cocaine-related overdose deaths reached 24,486 in 2021 (Spencer *et al.*, 2023).

Heroin, another highly addictive opioid, is associated with severe medical and social consequences, including hepatitis, HIV/AIDS, fetal complications, and increased crime and violence. In its pure form, heroin is a white that can be smoked or snorted, while the impure brownish variant is typically dissolved and injected (NIDA, 2021). In 2021, about 1.1 million people reported using heroin, with 1 million diagnosed with heroin disorder. That year, 26.000 people initiated heroin use, and heroin-related overdose deaths totaled 9,173 (SAMHSA, 2022; NIDA, 2024a).

Methamphetamine, a powerful stimulant developed from amphetamine in the early 20th century, is usually found as a crystalline white powder. While it initially increases energy, talkativeness, and euphoria, its misuse results in severe psychological and physical harm, contributing to crime, unemployment, and social problems. More than 16.8 million Americans aged 12 or older (6.0% of the population) have tried methamphetamine at least once, and in 2021, 2.5 million reported the use, with 1.6 million diagnosed with a methamphetamine use disorder. Methamphetamine-related overdose deaths were the highest among the substances considered, totaling 32,537 in 2021 (SAMHSA, 2022; Spencer *et al.*, 2023).

Finally, fentanyl has emerged as the most dangerous driver of overdose deaths. Originally developed for medical pain management, fentanyl is 50 to 100 times stronger than morphine. The greatest threat now comes from illegally manufactured fentanyl, often mixed with other substances or pressed into counterfeit pills, making it widespread and highly lethal. In 2022, synthetic opioids (excluding methadone) were involved in 68% of all drug overdose deaths. Nearly 74,000 deaths that year were attributed to synthetic opioids, marking a 5% increase from 2021 and a death rate nearly 24 times higher than in 2013 (NIDA, 2024b).

2.4 Research question

This study aims to investigate the relationship between subjective happiness and substance use. As discussed in previous sections, substance use is a multifaceted and complex behavior shaped by individual factors and broader social and familial dynamics. Reducing it to a few isolated factors risks producing misleading and inconsistent findings.

Over the past two decades, research on the relationship between happiness, life satisfaction, well-being and substance use behavior has yielded mixed results. While a general negative association is widely acknowledged (Zullig *et al.*, 2001; Razali *et al.*, 2015; Moschion & Powdthavee, 2017), the direct effect of subjective happiness as a determinant of substance use remains largely underexplored, and the causal direction of the relationship is still unclear. Some studies examine the impact of drug use on well-being (Maccagnan *et al.*, 2020), while others report no clear links. For instance, Mohamad *et al.* (2016) found no significant direct relationship between life satisfaction and substance abuse, although they observed a significant inverse relationship between life satisfaction and delinquency, which is an important intermediary factor positively associated with substance use. Similarly, Esposito *et al.*, (2020) reported no significant connections between life satisfaction and marijuana use among individuals aged between 15 to 20, and several large-scale surveys (ONS, 2020) describe associations without exploring causality or potential confounding.

This study addresses this gap by examining how subjective happiness influences the use of high-risk substances, with a specific focus on crack/cocaine and injection drug use – including substances such as heroin, cocaine, amphetamines, and steroids. A key methodological challenge is the possibility of endogeneity, particularly reverse causality: unhappy individuals may be more likely to use substances, while substance use may, in turn, reduce happiness. Although part of the existing literature supports the *social selection hypothesis* – suggesting that drug use contributes to unhappiness (Sachs, 2019; Kang, 2023) – this study posits an alternative and complementary perspective: that higher levels of subjective happiness may reduce the likelihood of substance use.

Furthermore, the existing literature on happiness as a predictor of substance use is often limited and outdated. Foundational research by Bachman (1979) explored this topic among general population, but more recent and large-scale analyses focusing specifically on happiness as a predictor of substance use remain scarce. Existing studies have primarily focused on specific subgroups, such as adolescents (Lew *et al.*, 2019), individuals in clinical settings, or vulnerable populations like youth in foster care (Kelly *et al.*, 2018; Long *et al.*, 2017). In contrast, the present study uses a broad and representative sample of the U.S. general population, allowing for more generalizable insights into how subjective happiness relates to substance use.

In this study, substance use is defined as the most recent use of substances prior to the interview, with a specific focus on crack/cocaine use and drug injection. The reference period ranges from more than three years ago to within the past 30 days. Drug consumption was assessed through methods such as smoking, snorting, and injecting. The analysis account for several moderating factors, including individual characteristics, socioeconomic status, life stressful events, social capital, and mental health status., which can either increase vulnerability to or protect against substance use.

The central hypothesis of this research is that higher level of subjective happiness decreases the likelihood of using these substances, in line with the *social causation hypothesis*. This view is grounded in the *eudaimonic perspective* of happiness (Deci & Ryan, 2008), which alludes to the fact that living a meaningful and purposeful life – supported by social relationships, positive emotions, and social support (Csikszentmihalyi *et al.*, 2014) – reduces the risk of substance use. Furthermore, Self-Determination Theory (SDT) indicates that fluctuations in the fulfillment of basic psychological needs – autonomy, competence, and relatedness – can influence the risk of developing substance use behaviors (Herchenroeder *et al.*, 2024).

Two main hypotheses are tested:

H-1: Higher levels of subjective happiness decrease the likelihood of using crack/cocaine and injecting drugs. Thus, happier individuals are less likely to engage in substance use.

H-2: Since a bidirectional relationship exists between subjective happiness and substance use, where substance use reduces happiness and lower happiness increases substance use, an instrumental variable approach – using social satisfaction and social trust as instruments – is applied to address endogeneity and isolate the causal effect of subjective happiness on substance use behaviors.

This study supports important policy implications: subjective happiness should be recognized as a key domain for public health interventions, reframing drug prevention from punitive measures to preventive strategies centered on well-being. Promoting happiness, reducing inequalities, and enhancing social integration through education, workplaces, and community initiatives can create protective and supportive environments substance use risk.

2.5 Data

The data for this study are sourced from the General Social Survey (GSS), a project of the NORC (National Opinion Research Center) at the University of Chicago. The GSS is an open-access database widely used for social research and public opinion studies, containing randomly selected observations of the American adult population aged 18 to more than 89 years old from 1972 up to 2022. Data are collected through various, including face-to-face interviews, web survey, phone calls, and multimodal approaches. For this study, only the 2018 and 2021 survey waves were utilized, as these years include the necessary set of variables for the analysis.

As shown in Table 2.1, the analysis relied on two slightly different samples from a total of 6,381 observations. Depending on the dependent variables, the sample included with 2,929 person-year observations for crack/cocaine use and 2,919 for drug injection. Additional information on missing values is provided in the Appendix (Table B.1).

2.5.1 Dependent variables

The NORC provides two ordinal discrete variables measuring substance use patterns over time: "*How long has it been since you last used 'crack' cocaine in chunk or rock form?*" and "*How long has it been since you last used a needle to inject drugs?*". For both questions, five response options are possible: 0 – "Never used", 1 – "More than 3 years ago", 2 – "More than 12 months ago but within the past 3 years", 3 – "More than 30 days ago but within the past 12 months", and 4 – "Within the past 30 days".

To address the instability in log-likelihood convergence due to limited observations and to obtain more reliable parameter estimates, levels 2 and 3 were combined, resulting in a new category that spans from more than 30 days up to 3 years. To compare the performance of both models before and after merging, a sensitive analysis was performed to confirm that the merged model indicates an improved fit and stability than the original one. Log-likelihood, Akaike's information criterion (AIC), and Bayesian information criterion (BIC) were performed to compare the models (Kuha, 2004). The log-likelihood for the crack/cocaine model was significantly improved at –295.6504 compared to –804.1799 for the original model. Also, the model fit enhanced, as indicated by a lower AIC (from 1646.36 to 629.30) and a lower BIC (from 1760.026 to 742.9666). Similarly, for the drug injection model, collapsing two levels of the dependent variable improved model performance. The log-likelihood increased from –620.9066 to –17.94402, while both AIC and BIC decreased substantially (from 1279.813 to 73.888 and from 1393.414 to 187.489), indicating a much better-fitting and more parsimonious specification.

The comparison of model fit indicators (AIC and BIC) suggests that the collapsed specification provides greater stability without altering the substantive results. For transparency, both the original and the collapsed OLS models are reported in Appendix (Table B.4, Table B.5), presenting estimates across specifications.

2.5.2 Independent variables

The literature identifies several indicators that influence vulnerability to substance use, from individual to socioeconomic characteristics.

In this study, the independent variable of interest is subjective happiness, measured through a single three-level question: "*Taken all together, how would you say things are these days?*" (1 = "Not too happy", 2 = "Pretty happy", 3 = "Very happy"). This is a standard item included in social surveys to capture self-reported well-being or life satisfaction and it is widely used in the literature. In the GSS, this indicator is collected annually and corresponds to Happy Life (O-HL) measure, coded as *O-HL-c-sq-v-3-aa* (Andrews & Withey, 1976).

The financial well-being of individuals was assessed through self-reported household income, based on the question: *"Compared with American families in general, would you say your family income is far below average, below average, average, above average, or far above average?"*. Responses are recorded on a five-point scale: 1 – "Far below average", 2 – "Below average", 3 – "Average", 4 – "Above average", and 5 – "Far above average". The relative income reflects how individuals perceive their household income in comparison to a broader reference group – a factor known to influence personal consumption and saving behaviors (Alvarez-Cuadrado & Van Long, 2011). It serves as a key indicator of perceived socioeconomic status, a factor consistently associated with substance use behaviors in various studies (Patrick *et al.*, 2012; Baptiste-Roberts & Hossain, 2018). For instance, metropolitan areas with greater income inequality often exhibit higher rates of drug use and a greater incidence of infectious diseases among drug users (Friedman *et al.*, 2016). Another study demonstrated that individuals who use drugs tend to report lower average monthly incomes compared to non-users (Long *et al.*, 2014). Following the approach of Sabatini (2014), household income was treated as a continuous variable to enable more precise analysis.

Education level and school environments play a significant role in shaping the likelihood of substance use. Research by Fletcher *et al.* (2008) found that positive school environments reduce youth drug use, whereas poor school engagement – such as skipping classes, suspensions, or early academic underachievement – aligns with a higher risk of developing substance use disorders later in life (Fothergill *et al.*, 2008). Not completing high school further increases this risk by three to four times compared to earning a college degree. Yet, Jinez *et al.* (2009) observed that prolonged school attendance may also raise the likelihood of substance use, possibly due to stronger peer influence and weaker family ties. Education interacts with socioeconomic status as well: wealthier students show a higher risk of binge drinking, marijuana, and cocaine use, a dimension often overlooked in prevention programs (Humensky, 2010; Martin, 2019). Moreover, schools with strong anti-drug norms act as protective environments, while more tolerant cultures increase the chance of smoking, alcohol, and marijuana use (Kumar *et al.*, 2002). In this study, education level is included as a continuous variable. The original scale ranged from level 0 ("no formal schooling") to 20 ("8 or more years of college"). To address outliers and sparse categories, the variable was recoded into 12 aggregated levels, improving balance across groups and enhancing the stability of statistical estimates.

Regarding life stressors during adolescence, several variables are included in the model. Family structure at age 16 was assessed through the question: "*Were you living with both your own mother and father around the time you were 16?*". Responses distinguished between different arrangements, such as living with both biological parents, a single parent, stepparents, other relatives, or alternative arrangements. From this, a dummy variable was created to indicate whether respondents lived with both biological parents at age 16. To capture the reasons for not doing so, an additional question asked: "*If not living with both own mother and father: What happened?*". Two dummy variables were derived: (*i*) "one or both parents died" and (*ii*) "parents divorced or separated". Adolescent socioeconomic conditions were also considered. Household income relative to the national average at age 16 was measured on a five-point scale (from "*far below average*" to "*far above average*"). Finally, place of residence at age 16 was classified using the question: "*Which of these categories comes closest to the type of place you were living in when you were 16 years old?*". Taking "*living in a medium-sized city (50,000-250,000)*" as the reference, three dummy variables were constructed: (*i*) "*living in a suburb near a large city or in a large city (over 250,000)*", (*ii*) "*small city or town (under 50,000 inhabitants)*", and (*iii*) "*living in open country or on a farm*". The last two categories – living in open country or on a farm – were merged due to conceptual similarity and small sample sizes.

Finally, a set of controls was included to account for potential confounding factors. Gender was measured with a dummy variable for male respondents. Age was treated as a continuous variable ranging from 18 to 89 years, with observations above 89 excluded to improve data reliability; an age-squared term was also introduced to capture potential non-linear effects. Ethnicity was coded into three categories, with two dummy variables identifying Black and other racial groups, and White serves as the reference category. In addition, following Shih *et al.* (2010), who reported higher rates of lifetime and past-month substance use among Hispanics, a dummy variable was added for respondents identifying as Latino.

Table 2.1: Descriptive statistics

	Crack/cocaine use (2,929 obs.)		Injection drug use (2,919 obs.)		
Variables	Mean	Std. Dev.	Mean	Std. Dev.	Min./Max.
Male	0.467	0.499	0.468	0.499	0/1
Age	50.582	17.598	50.580	17.600	18/88
White	0.791	0.407	0.792	0.406	0/1
Black	0.113	0.317	0.113	0.316	0/1
Other	0.096	0.294	0.096	0.294	0/1

Hispanic	0.116	0.320	0.116	0.320	0/1
Years of education	6.665	2.557	6.670	2.558	1/12
Current family income	2.944	0.942	2.945	0.942	1/5
Subjective happiness	2.034	0.666	2.034	0.667	1/3
Very happy	0.240	0.427	0.240	0.427	
Pretty happy	0.555	0.497	0.554	0.497	
Not too happy	0.205	0.404	0.206	0.404	
Living in a small town at 16yo	0.318	0.466	0.319	0.466	0/1
Living in a large town at 16yo	0.167	0.372	0.166	0.373	0/1
Living in a suburb at 16yo	0.174	0.379	0.174	0.379	0/1
Living in open country/farm at 16yo	0.157	0.364	0.157	0.363	0/1
Living with both parents at 16yo	0.788	0.409	0.788	0.409	0/1
Separated or divorced parents at 16yo	0.125	0.331	0.126	0.332	0/1
One or both parents died at 16yo	0.041	0.197	0.040	0.197	0/1
Family income at 16yo	2.814	0.925	2.814	0.926	1/5
Lifetime use of drugs	0.047	0.211	0.026	0.159	0/1
Last time use of drugs					0/3
Never used	0.962	0.192	0.974	0.159	
More than 3 years ago	0.038	0.192	0.017	0.131	
More than 30 months ago but within the past 3 years	0.007	0.086	0.006	0.080	
Within the past 30 days	0.001	0.032	0.002	0.045	
Satisfaction with social relationships	3.353	1.032	3.350	1.034	1/5
Social trust	1.799	0.922	1.798	0.921	1/3

2.6 Econometric models

2.6.1 General model

To investigate the factors influencing substance use behaviors, two complementary econometric approaches were employed: Ordinary Least Squares (OLS) and Ordered Probit (OP) models. Each model provides a distinct interpretation of the relationships and contributes to a robust analysis of the empirical framework.

In the first model, OLS regressions were estimated to obtain preliminary insights. In the second model, OP regressions were employed to preserve the ordered structure of the dependent variables. This approach assumes the existence of an unobserved continuous latent variable Y_i^* underlying the observed ordinal variable Y_i, which is linearly related to the independent variables. The OP was estimated using Maximum Likelihood Estimation (MLE), with coefficients interpreted as the direction and strength of associations.

Based on the research question, the empirical specification for both substance use behaviors was modeled as follows:

$$\mathrm{Y}_{i,t} = \beta_0 + \beta_1 \mathrm{Happiness}_{i,t} + \mathrm{X}'_{i,t}\beta + \varepsilon_{i,t}$$

where $\mathrm{Y}_{i,t}$ represents the substance use outcome – either crack/cocaine or drug injection – for individual i at time t. $\mathrm{Happiness}_{i,t}$ is an ordinal independent variable capturing subjective happiness.

$X'_{i,t}$ is a vector of sociodemographic, socioeconomic, and family background controls, and $\varepsilon_{i,t}$ is the error term.

2.6.2 IV approach

To address potential endogeneity arising from bidirectionality or simultaneity between subjective happiness and substance use, Two-Stage Least Squares (2SLS) and Two-Stage Residuals Inclusion (2SRI) estimators were employed.

2.6.2.1 2SLS

In the first analysis, 2SLS regressions were estimated treating both dependent variables as continuous. In the first stage, subjective happiness was regressed on the instrumental variables (IVs) and other exogenous covariates to generate predicted values; more details regarding first stage estimates are presented in Table B.7, Table B.9, Table B.11 in the Appendix. In the second stage, these predicted values replaced the original endogenous happiness variable to estimate the causal effect on substance use. This method corrects for endogeneity under the assumption that the IVs are strongly correlated with happiness but uncorrelated with the error term in the second stage (Angrist & Pischke, 2008). Robust standard errors were used to correct for potential heteroskedasticity.

(i) First stage: modeling the relationship between Happiness, IVs, and controls

$$\text{Happiness}^*_{i,t} = \gamma' \text{X}_{i,t} + \beta_1 \text{IV}^1_{i,t} + \beta_2 \text{IV}^2_{i,t} + \varepsilon_{i,t}$$

$$\text{with Happiness}_{i,t} = \begin{cases} 1 \text{ if } \quad \text{Happiness}^*_{i,t} \leq \tau_1 \\ 2 \text{ if } \tau_1 < \text{Happiness}^*_{i,t} \leq \tau_2 \\ 3 \text{ if } \quad \text{Happiness}^*_{i,t} > \tau_2 \end{cases}$$

where $\text{Happiness}^*_{i,t}$ is the latent continuous variables, $\text{Happiness}_{i,t} \in \{1, 2, 3\}$ is the observed ordinal level (1 – "Not too happy", 2 – "Pretty happy", 3 – "Very happy"), and τ_1, τ_2 are thresholds. $\text{IV}^1_{i,t}$and $\text{IV}^2_{i,t}$ capture satisfaction with social relationships and trust in others. $\text{X}_{i,t}$ is the vector of control, and $\varepsilon_{i,t}$ is the error term.

(ii) Second stage: estimating the substance use equations with fitted happiness values (2SLS)

$$Y^*_{i,t} = \beta_1 + \kappa \widehat{\text{Happiness}}_{i,t} + \gamma' \text{X}_{i,t} + \varepsilon_{i,t}$$

where $\text{Y}^*_{i,t}$ represents the latent propensity for substance use, $\widehat{Happiness}$ are the fitted from the first stage, and κ corrects for endogeneity. $\text{X}_{i,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term.

2.6.2.2 2SRI

In the second analysis, the ordinal nature of the dependent variables was preserved by applying the 2SRI approach (Terza *et al.*, 2008; Terza, 2017). In this method, the first stage consists of an auxiliary regression of the endogenous variable – subjective happiness – on the instrumental variables (social satisfaction and social trust) and other exogenous covariates. From this regression, the predicted residuals are obtained.

Unlike 2SLS, where the endogenous variable is replaced by its fitted values, the 2SRI retains the original variable and adds the first stage residuals as an additional regressor in the second stage (Wooldridge, 2010). This allows the use of an Ordered Probit model in the second stage, preserving the ordinal structure of the outcome and improving consistency and efficiency of the estimates. To further account for model misspecification and sampling variability, bootstrapped standard errors were employed.

(iii) Second-stage: estimating the substance use equations with predicted residuals (2SRI)

$$Y_{i,t}^{*} = \beta_0 + \beta_1 \mathrm{Happiness}_{i,t} + \kappa \widehat{\mathrm{Residual}}_{\mathrm{Hap}_{(i,t)}} + \gamma' \mathrm{X}_{i,t} + \varepsilon_{i,t}$$

where $Y_{i,t}^{*}$ represents the latent propensity for substance use representing the observed ordinal outcome. $\mathrm{Happiness}_{i,t}$ is the observed happiness variable. $\widehat{\mathrm{Residual}}_{\mathrm{Hap}_{(i,t)}}$ are the predicted residuals from the first stage regression, κ corrects for endogeneity, $\mathrm{X}_{i,t}$ is a vector of control variables. $\varepsilon_{i,t}$ is the error term.

2.7 Preliminary findings

Preliminary findings from OLS and Ordered Probit (OP) models suggested robust negative associations between subjective happiness and substance use behaviors. As displayed in Table 2.2 and Table 2.3, both modeling approaches were applied to two dependent variables: crack/cocaine use and injection drug use. The consistency between the two specifications provided reassurance regarding the robustness of the results. Given the ordinal nature of the outcome variables, the interpretation below focused primarily on the OP model results.

The analysis revealed a statistically significant negative association between subjective happiness and both types of substance use. Specifically, a one-unit increase in happiness is liked to a reduction in the severity of crack/cocaine use (β = –0.187, p = 0.004). A similar effect is observed for injection drug use (β = –0.218, p = 0.006). These results support the *social causation hypothesis* and point to a clear trend: individuals reporting higher levels of subjective happiness are less prone to substance use, indicating that well-being may function as a protective factor against substance-related risks.

These findings align with prior studies revealing an association between substance use and diminished life satisfaction. For instance, Zullig et al. (2001) reported that various substance use behaviors, including crack/cocaine consumption and injection drug use, were significantly associated with lower life satisfaction among adolescents. Their models identified particularly elevated risks among Black males, with the highest overall odds ratios reported for lifetime injection drug use (*OR* = 11.79), lifetime crack or freebase cocaine use (*OR* = 3.43), and cocaine use in the past 30 days (*OR* = 2.85). Evidence also suggests that declines in subjective well-being may precede engagement in substance use. Moschion & Powdthavee (2017), for example, demonstrated that a drop in life satisfaction often occurs before the initiation of street drug use, especially among disadvantaged populations. Similarly, Lew et al. (2019) found that life satisfaction levels predicted marijuana use among adolescents: those with moderate satisfaction (scores 5-6) had an odds ratio of 1.16, while those with low satisfaction (scores ≤ 4) showed a significantly higher odd ratio of 1.98. Taken together, these results reinforce the idea that happiness and well-being are not only outcomes affected by substance use, but also antecedent conditions shaping such behaviors. This perspective is consistent with the *social causation hypothesis*, which posits that positive psychosocial experiences can reduce vulnerability to crack/cocaine use and injection drug use.

Socioeconomic factors also emerged as further determinants of substance use. Current family income reports a strong negative association with both substance use outcomes (crack/cocaine use: $\beta = –0.213$, $p < 0.000$; drug injection: $\beta = –0.160$, $p = 0.007$), indicating that individuals with higher perceived family income are less likely to engage in substance use behaviors. This finding is in line with prior research demonstrating that lower financial and economic status increases the risk of substance use (Baptiste-Roberts & Hossain, 2018), as drug users often report lower monthly incomes than non-users due to the economic instability linked to illicit drug use (Long *et al.*, 2014). By contrast, a higher family income at age 16 was positively associated with crack/cocaine use ($\beta = 0.111$, $p = 0.022$) but had no significant effect on drug injection. This pattern underlines adolescence as a critical stage for the initiation of drug use, with evidence proposing that wealthier adolescents are more susceptible to engaging in risky behaviors such as binge drinking, marijuana use, and cocaine consumption (Humensky, 2010; Martin, 2019).

Another significant factor was educational attainment. It is negatively related with both substance use outcomes, supporting the hypothesis that education serves as a protective factor. Individuals with more years of education are less likely to engage in substance use (crack/cocaine use: $\beta = –0.071$, $p < 0.000$; drug injection: $\beta = –0.065$, $p = 0.005$). For instance, Fletcher *et al.* (2008) found that fostering school ethos and addressing student dissatisfaction can lower the risk of youth drug use. Fothergill *et al.* (2008) demonstrated that poor academic performance in the first grade significantly predicted drug use disorders more than 25 years later, and that those who did not complete high school were three to four times more likely to develop drug use disorders compared to those who attained a college degree.

In addition to socioeconomic indicators, the analysis considered variables related to the adolescent family environment and geographical contexts. Living with both biological parents at age 16 corresponds to a lower likelihood of crack/cocaine use in the past 30 days ($\beta = –0.309$, $p = 0.068$). A stable family environment with positive parent-child relationships appears protective, consistent with Stewart (2023), who found that adolescents with warm, supportive relationships with their mothers were less likely to use substances, while strong bonds with fathers reduced the specific risk of crack and alcohol use.

Geographical residence during adolescence also revealed significant associations. Individuals who resided in a large town ($\beta = 0.347$, $p = 0.019$) or in suburban areas ($\beta = 0.369$, $p = 0.014$) have a higher probability of crack/cocaine use, whereas living in open country or on a farm appears protective against drug injection ($\beta = –0.557$, $p = 0.026$). However, literature presents mixed findings on the rural-urban divide in substance use. Gfroerer *et al.* (2007) reported that adult in rural counties generally had lower rates of substance use compared to metropolitan adults, although rural and urbanized nonmetropolitan areas showed higher methamphetamine use. In contrast, McInnis *et al.* (2015) and Lenardson *et al.* (2020) found minimal differences between rural and urban populations, suggesting that geographical effects are complex and potentially mediated by other factors.

With respect to demographic factors, gender and ethnicity displayed notable patterns. Being male increases the probability of using crack/cocaine ($\beta = 0.166$, $p = 0.054$). This finding is coherent with existing research, which indicates that men are generally more prone to illicit drug use and dependence on both drugs and alcohol compared to women across most age groups (NIDA, 2020). Also, being Hispanic influences substance use, decreasing the likelihood of recent substance use in both models (crack/cocaine use: β = –0.269, p = 0.094; drug injection: β = –0.470, p = 0.021). This finding contrasts with previous evidence reporting higher substance use rates among Hispanics (Shih *et al.*, 2010).

Finally, although the effect size is minimal, the age-squared variable exhibited a negative and statistically significant coefficient across both regression models. This pattern points to the fact that substance use may decline with age, especially in later adulthood, adding a potential non-linear dynamic in the influence of life-course factors on substance use behavior. Consistently, Stewart *et al.* (2020) – reviewing substance use across the lifespan – found that adolescence and emerging adulthood are critical phases of heightened experimentation, whereas in middle and later adulthood substance use become less common, with alcohol-related behaviors more prevalent and, in some cases, late-onset disorders emerging in connection with social or health stressors.

Table 2.2: The OLS and Ordered Probit estimates for crack/cocaine use

	OLS			Ordered Probit		
	β	*SE*	p	β	*SE*	p
Constant	0.211	0.039	0.000***			
Male	0.016	0.010	0.113	0.166	0.086	0.054*
Age	–0.000	0.000	0.141	–0.006	0.003	0.029**
Age^2	–0.000	0.000	0.001***	–0.001	0.000	0.000***
White	0.005	0.018	0.775	0.033	0.167	0.845
Black	0.018	0.023	0.431	0.120	0.196	0.540
Hispanic	–0.029	0.017	0.097*	–0.269	0.161	0.094*
Years of education	–0.007	0.002	0.002***	–0.071	0.019	0.000***
Current family income	–0.026	0.006	0.000***	–0.213	0.049	0.000***
Subjective happiness	–0.020	0.007	0.007***	–0.187	0.065	0.004***
Living in a small town at 16yo	0.014	0.015	0.338	0.187	0.136	0.168
Living in a large town at 16yo	0.031	0.017	0.070*	0.347	0.147	0.019**
Living in suburb at 16yo	0.034	0.017	0.044**	0.369	0.151	0.014**
Living in open country/on a farm at 16yo	0.017	0.017	0.319	0.172	0.160	0.284
Living with both parents at 16yo	–0.050	0.025	0.044**	–0.309	0.170	0.068*
Divorced or separated parents at 16yo	0.016	0.027	0.549	0.130	0.182	0.475
One or both parents died at 16yo	–0.019	0.034	0.567	–0.088	0.247	0.720
Family income at 16yo	0.012	0.005	0.042**	0.111	0.048	0.022**
0|1				0.529	0.311	
1|2				1.300	0.317	
2|3				2.031	0.356	
Obs.			*2,929*			
Multiple R^2		*0.03606*				
Adjusted R^2		*0.03043*				
Pseudo R^2					*0.0981*	
F-statistic		*6.405****				

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table 2.3: The OLS and Ordered Probit estimates for injection drug use

	OLS			Ordered Probit		
	β	*SE*	*p*	*β*	*SE*	*p*
Constant	0.212	0.050	0.000***			
Male	–0.000	0.009	0.997	0.026	0.104	0.805
Age	–0.001	0.000	0.005***	–0.006	0.003	0.057*
Age^2	–0.000	0.000	0.208	–0.000	0.000	0.068*
White	–0.001	0.015	0.936	–0.076	0.184	0.677
Black	–0.017	0.023	0.468	–0.339	0.236	0.151
Hispanic	–0.042	0.013	0.002***	–0.470	0.203	0.021**
Years of education	–0.005	0.002	0.004***	–0.065	0.023	0.005***
Current family income	–0.015	0.005	0.006***	–0.160	0.059	0.007***
Subjective happiness	–0.021	0.007	0.004***	–0.218	0.079	0.006***
Living in a small town at 16yo	0.004	0.014	0.744	0.098	0.150	0.511
Living in a large town at 16yo	0.013	0.017	0.436	0.204	0.171	0.232
Living in suburb at 16yo	0.015	0.016	0.358	0.223	0.169	0.187
Living in open country/on a farm at 16yo	–0.032	0.012	0.008***	–0.557	0.250	0.026**
Living with both parents at 16yo	–0.034	0.033	0.299	–0.254	0.203	0.210
Divorced or separated parents at 16yo	–0.029	0.035	0.417	–0.122	0.223	0.585
One or both parents died at 16yo	–0.001	0.047	0.973	–0.036	0.290	0.900
Family income at 16yo	–0.003	0.005	0.550	0.005	0.059	0.928
0|1				0.322	0.359	
1|2				0.806	0.362	
2|3				1.347	0.377	
Obs.	*2,919*					
Multiple R^2		*0.0229*				
Adjusted R^2		*0.01718*				
Pseudo R^2					*0.0775*	
F-statistic		*0.0017****				

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

2.8 Instruments

As outlined in the previous sections, the relationship between subjective happiness and substance use may be subjected to endogeneity due to reverse causality. Endogeneity arises when the predictor (x) is correlated with the error term (ε) in a regression model, violating the OLS assumption for which the error term must be uncorrelated with the predictor ($\mathrm{Cov}(x, \varepsilon) = 0$). To mitigate this issue, the inclusion of one or more instrumental variables is a standard approach to control for confounding factors, measurement error, and omitted variables bias (Greene, 2012). For an instrumental variable to be valid, it must satisfy two critical conditions: *relevance*, meaning the instrument must be strongly correlated with the endogenous variable, and *orthogonality* – or exclusion restriction – meaning the instrument must be uncorrelated with the model's error term (Angrist & Pischke, 2008).

In this study, two instrumental variables (IVs) related to social capital – *social satisfaction* and *social trust* – were introduced to address endogeneity concerns. Subjective happiness, the endogenous variable of interest, has been extensively linked to various dimensions of social capital in existing literature. These two IVs are conceptually distinct but empirically interrelated, both representing core elements that shape individuals' states of happiness and well-being (Bartolini & Sarracino, 2011;

Rodríguez-Pose & von Berlepsch, 2014; Majeed & Samreen, 2021; Lee & Bae, 2022; Gómez-Balcácer *et al.*, 2023). The effectiveness of using social satisfaction and social trust as IVs in health-related studies has been well-documented by Sabatini (2014) and Kyriopoulos *et al.* (2018), who investigated the impact of subjective happiness on health outcomes in Italy and Greece, respectively.

To test empirically relevance and orthogonality of both instruments, diagnostic tests from the OLS models were examined.

The *relevance* condition is strongly supported by the weak instrument tests, which produced highly significant F-statistics of 285.23 ($p < 0.001$) for the crack/cocaine model and 283.786 ($p < 0.001$) for the drug injection model. An F-statistic substantially greater than the conventional threshold of 10.0 indicates the instruments are robust and relevant. Additionally, the very *low p-values* further confirm the strength and validity of the instruments (Staiger & Stock, 1997; Andrews *et al.*, 2019). Moreover, the Wu-Hausman test was conducted to assess whether the use of instrumental variables was necessary by testing for endogeneity. The results showed no statistically significant evidence of endogeneity, with test statistics of 1.813 ($p = 0.178$) for the crack/cocaine model and 0.397 ($p = 0.528$) for the drug injection model. These non-significant *p-values* imply that OLS and IV estimates do not differ significantly, implying that the IV approach may not be strictly required. The statistical absence of endogeneity is further supported by the non-significance of the residual terms included in the 2SRI. Nonetheless, the IV models were retained to ensure consistency and robustness, and to correct for potential unobserved confounding or omitted variable bias (Sande & Ghosh, 2018).

The *orthogonality* condition was also empirically assessed. The Sargan-Hansen test (Sargan, 1958; Hansen, 1982) produced test statistics of 0.760 ($p = 0.383$) for the crack/cocaine model and 0.123 ($p = 0.726$) for the drug injection model. These relatively high p-values suggest that the instruments are uncorrelated with the error term, supporting their validity (Wooldridge, 2010). However, as Kiviet & Kripfganz (2021) note, a *p-value* above 0.50 is ideal to fully confirm orthogonality. In the case of the crack/cocaine model, the *p-value* of 0.383 indicates moderate but not conclusive evidence of instrument validity under this more conservative standard. Nevertheless, both values are considered acceptable within conventional econometric practice – with a threshold of $p > 0.05$ – and fail to reject the null hypothesis of instrument validity under the exclusion restriction.

2.8.1 Social satisfaction

The first instrument used in this study is social satisfaction, which measures individual contentment with social activities and relationships within a community. This measure is derived from the NORC database through the question: "*In general, how would you rate your satisfaction with your social activities and relationships?*" with five response options: 1 – "Poor", 2 –"Fair", 3 – "Good", 4 – "Very good", and 5 – "Excellent." Social satisfaction reflects the fulfillment individuals derive from interpersonal relationships, grounded in supportive, respectful, and cooperative interactions (Geyskens & Steenkamp, 2000; Kelly *et al.*, 2017). This concept is closely linked to bonding social capital, which captures the strength and density of close community relationships (Zhang *et al.*, 2011; Growiec & Growiec, 2013).

The relevance condition for social satisfaction as an instrumental variable is supported by theoretical foundations. High-quality social interactions with friends, relatives, neighbours, and colleagues are strongly correlated with overall life satisfaction (Amati *et al.*, 2018). Diener & Seligman (2002) found that individuals with satisfying social relationships report greater happiness and spend less time alone. Similarly, Helliwell & Putnam (2004) observed that frequent social interactions consistently enhance subjective well-being across cultures. Haller & Hadler (2008) further demonstrated that those involved in close, supportive relationships experience higher happiness levels than socially isolated individuals. Several studies also establish a causal link between social satisfaction and life satisfaction. Becchetti *et al.* (2008), analyzing 21 years of data from the German Socio-Economic Panel (GSOEP), found that engaging in non-instrumental social activities – such as volunteering, social events, and spending time with friends – significantly improves life satisfaction, particularly for women, older adults, and the less educated. Bruni & Stanca (2008), using data from 34,962 observations in the World Values Survey, highlighted that spending time with family, friends, and in service organizations, has a strong positive effect on life satisfaction, with family interactions having the greatest impact. More recently, Ascigil *et al.* (2023) used an instrumental variable approach to examine how brief social exchanges with weak ties and strangers influence well-being. Data from 3,266 observations in Turkey and 60,141 in Western countries revealed that simple social exchanges – such as greetings or short conversations – significantly boost life satisfaction.

Concerning orthogonality, a key component of social satisfaction is social support, which reflects the perceived availability of emotional, instrumental, and informational assistance from one's social network. Extensive research has shown a strong positive relationship between social support and both life satisfaction and subjective happiness (North *et al.*, 2008; Dominguez-Fuentes & Hombrados-Mendieta, 2012; Moeini *et al.*, 2018; Ayllón-Negrillo *et al.*, 2024). Yang *et al.* (2018) investigated how social support and resilience mediate the relationship between stress and life satisfaction in individuals with substance use disorders. Using the Multidimensional Scale of Perceived Social Support (MSPSS), they identified two significant pathways: (*i*) social support alone directly enhanced life satisfaction (0.0696), and (*ii*) a combined effect of social support and resilience further amplified life satisfaction (0.0785). Cao & Zhou (2019) also found that social support had both a direct (0.65) and an indirect (0.45) effect on life satisfaction among people with substance use disorders, with the latter partially mediated by resilience. Expanding on this, Yang *et al.* (2022) demonstrated that social support strengthens resilience, which improves positive affect and ultimately increases life satisfaction. They identified two additional pathways (*i*) social support directly fosters resilience, leading to greater life satisfaction (0.26), and (*ii*) social support indirectly enhances life satisfaction by boosting resilience and positive emotions (0.17). These findings highlight the essential role of social support – a key element of social satisfaction – in fostering life satisfaction and subjective happiness, particularly among individuals with substance use disorders. Higher levels of social support foster resilience and enhance positive emotional well-being, which indirectly lowers the risk of substance use. This relationship confirms that social satisfaction impacts substance use indirectly through its effect on subjective happiness, thereby satisfying the orthogonality condition. Consequently, effective initiatives that strengthen social relationships and networks not only improve overall well-being but also serve as effective strategies for preventing and reducing substance use.

2.8.2 Social trust

The second instrumental variable employed in the model is social trust, another key component of social capital. Unlike institutional trust, which reflects confidence in public or private institutions (Hudson, 2006), social trust measures individuals' belief that others are generally trustworthy and unlikely to cause harm – either intentionally or unintentionally – and may even act in their best interest (Newton, 2001).

In this study, social trust is assessed through the question: '*Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?*', respondents selected from three ordinal responses: 1 – "Can't be too careful", 2 – "Depends", and 3 – "Can trust". The *relevance* condition for social trust as an instrument is supported by the existing literature. Numerous studies have identified a positive causal relationship between social trust and subjective happiness, life satisfaction (Tokuda *et al.*, 2010; Bartolini *et al.*, 2016), and overall well-being (Helliwel & Putnam, 2004). Specifically, Bjørnskov (2008) identified a strong positive externality of social trust in promoting happiness after addressing endogeneity. Kuroki (2011), using data from Japan, found a significant positive effect of social trust on individual happiness. Growiec & Growiec (2014) explored how bridging and bonding social capital, social trust, and income collectively influence self-reported happiness. They identified a "low-trust trap" in Central and Eastern European countries, where persistently low social trust and weak social networks contribute to sustained low levels of happiness. Similarly, Lu *et al.* (2020) established a causal positive effect of social trust on individual happiness in China, using longitudinal data and robust instrumental variables. They also demonstrated heterogeneity in this effect: social trust had a stronger positive impact on the happiness of males and urban residents.

Regarding *orthogonality*, several studies have explored the relationship between social trust and substance use (Lundborg, 2005; Wray-Lake *et al.*, 2012; Åslund & Nilsson, 2013; Pourramazani *et al.*, 2018). While these studies provide significant evidence that social trust influences substance use, none have established a clear causal or direct link between social trust and substance use behaviors, particularly regarding behaviors like crack/cocaine use and drug injection. Some research has also focused on legal substances. For instance, Johnell *et al.* (2006) examined the impact of "miniaturization of community" – communities with high social participation but low trust – on the use of prescribed anxiolytic and hypnotic drugs. Similarly, Takakura (2011) explored whether school-based social trust influences smoking and drinking behaviors among Japanese students, and Jang-Rak *et al.* (2020) found correlations between generalized trust and alcohol use disorders. However, no studies to date have employed instrumental variable approaches or panel datasets to investigate the impact of social trust on substance use, leaving the causal pathway unclear. For example, Saltkjel (2009) studied 80 welfare recipients in Norway and found that drug use – reported in 70 observations – negatively impacted social trust, highlighting the unclear directionality of this relationship. Additionally, prior studies have not accounted for subjective happiness or life satisfaction – factors shown to be significantly influenced by social trust. This omission could result in biased findings and limit a clear understanding of how social trust affects substance use. Without considering mediators like subjective happiness or life satisfaction, the impact of social trust on substance use may be overestimated. Further complicating the issue is the variation in how social trust is conceptualized across studies. For example, Bartkowski & Xu (2007) differentiated between "*theistic trust*" (trust in God) and "*humanistic trust*" (trust in people) when analyzing the influence of religiosity on teen substance use. Similarly, Yang *et al.* (2020) used a composite index of social trust that encompassed trust in medical institutions, social organizations, government, hard work, and talented individuals. These differing interpretations make it more challenging to isolate a direct impact of social trust on substance use, demonstrating the complexity of the relationship.

In sum, both instruments satisfy the key econometric assumptions of *relevance* and *orthogonality*. Conventional diagnostic test indicated strong instrument relevance and failed to reject the null hypothesis of validity under the exclusion restriction. While one model did not fully meet the more restrictive threshold suggested by Kiviet & Kripfganz (2021), the results remain consistent with standard econometric practice, supporting the robustness of the chosen instruments.

2.9 IV model results

2.9.1 2SLS and 2SRI results

Table 2.4 and Table 2.5 present the second stage results from the instrumental variable (IV) estimations using both the 2SLS and 2SRI models. While the 2SLS estimates serve as a robustness check validating the strength and exogeneity of the instruments, the 2SRI provides a more stable estimator under the non-linear structure of the outcome variables, capturing variation across levels of substance use severity. Moreover, the use of bootstrap standard errors enhances the precision and reliability of inference. For transparency, estimates without bootstrapped SEs are presented in the Appendix (Table B.8).

After accounting for endogeneity, the estimated effect of subjective happiness on substance use becomes stronger across both modeling approaches. In the OLS framework, the coefficient for happiness increases the magnitude from –0.020 to –0.046 (p = 0.039) for crack/cocaine use and from –0.021 to –0.031 (p = 0.096) for drug injection, indicating a more pronounced protective effect. In the Ordered Probit estimates, the changes are even more substantial: the coefficient for crack/cocaine use shifts from –0.187 (p = 0.004) to –0.353 (p = 0.046), and from –0.218 (p = 0.006) to –0.459 (p = 0.018) for drug injection. These results indicate that the IV approach improves the estimations of the effect of subjective happiness on both outcomes.

Consistent with the primary hypothesis, both IV models confirm a negative and statistically significant association between subjective happiness and substance use behaviors, as previously observed in the preliminary results. The larger coefficient magnitudes indicate that failing to account for endogeneity may substantially underestimate the causal impact of subjective happiness on substance use, indicating a more decisive role then initially apparent. Although significance levels shifted from the 1% to the 5% threshold, the persistence of statistical significance reinforces the robustness of these findings and highlights the importance of subjective happiness as a protective factor against substance use.

By correcting for endogeneity, these results provide robust empirical evidence of the protective influence of subjective happiness in mitigating high-risk substance use behaviors, with important implications for public health interventions and policy design.

Table 2.4: The OLS and Ordered Probit estimates with IVs for crack/cocaine use

	OLS			Ordered Probit		
	β	*SE*	*p*	*β*	*SE*	*p*
Constant	0.253	0.060	0.000***			
Male	0.015	0.010	0.118	0.163	0.087	0.062*
Age	–0.000	0.000	0.151	–0.006	0.003	0.050*
Age^2	–0.000	0.000	0.001***	–0.001	0.000	0.000***
White	0.004	0.016	0.788	0.028	0.176	0.874
Black	0.016	0.024	0.491	0.107	0.200	0.593
Hispanic	–0.026	0.016	0.099*	–0.248	0.172	0.149
Years of education	–0.006	0.002	0.000***	–0.071	0.019	0.000***

Current family income	–0.022	0.007	0.001***	–0.194	0.054	0.000***
Subjective happiness	–0.046	0.022	0.039**	–0.353	0.177	0.046**
Living in a small town at 16yo	0.015	0.013	0.244	0.200	0.140	0.155
Living in a large town at 16yo	0.032	0.018	0.082*	0.353	0.154	0.022**
Living in suburb at 16yo	0.034	0.016	0.040**	0.368	0.147	0.012**
Living in open country/on a farm at 16yo	0.018	0.016	0.249	0.182	0.156	0.243
Living with both parents at 16yo	–0.047	0.031	0.126	–0.290	0.165	0.079*
Divorced or separated parents at 16yo	0.019	0.037	0.609	0.148	0.177	0.401
One or both parents died at 16yo	–0.013	0.043	0.756	–0.050	0.371	0.893
Family income at 16yo	0.011	0.005	0.038**	0.109	0.047	0.020**
0|1				0.263	0.434	
1|2				1.034	0.426	
2|3				1.769	0.463	
$\text{Residuals}_{HAPPINESS}$				0.199	0.186	0.284
Observations			2,929			
Weak instruments	*285.23*		*0.000****			
Wu-Hausman	*1.813*		*0.178*			
Sargan-Hansen	*0.760*		*0.383*			
Multiple R^2 or Pseudo R^2		*0.0324*			*0.0992*	

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*
Robust standard errors were computed for both OLS models the Breusch-Pagan test indicated the presence of heteroskedasticity, violating the constant variance assumption of the error terms. Bootstrap standard errors with relative p-values were computed for the Ordered Probit model. The Variance Inflation Factor (VIF) test revealed no evidence of multicollinearity across the models.

Table 2.5: The OLS and Ordered Probit estimates with IVs for injection drug use

	OLS			Ordered Probit		
	β	*SE*	*p*	*β*	*SE*	*p*
Constant	0.229	0.056	0.000***			
Male	0.000	0.009	0.983	0.026	0.106	0.807
Age	–0.001	0.000	0.005***	–0.006	0.003	0.063*
Age^2	0.000	0.000	0.190	–0.000	0.000	0.049*
White	–0.001	0.015	0.918	–0.080	0.229	0.726
Black	–0.017	0.023	0.445	–0.348	0.282	0.216
Hispanic	–0.041	0.014	0.002***	–0.450	0.326	0.168
Years of education	–0.005	0.002	0.004***	–0.064	0.024	0.007***
Current family income	–0.014	0.006	0.021**	–0.133	0.066	0.042**
Subjective happiness	–0.031	0.014	0.096*	–0.459	0.193	0.018**
Living in a small town at 16yo	0.005	0.017	0.712	0.108	0.162	0.505
Living in a large town at 16yo	0.014	0.016	0.420	0.205	0.183	0.261
Living in suburb at 16yo	0.015	0.012	0.359	0.214	0.183	0.243
Living in open country/on a farm at 16yo	–0.032	0.033	0.010**	–0.560	0.720	0.437
Living with both parents at 16yo	–0.033	0.035	0.313	–0.219	0.222	0.323
Divorced or separated parents at 16yo	–0.027	0.046	0.434	–0.095	0.235	0.685
One or both parents died at 16yo	0.001	0.004	0.982	0.041	0.674	0.951
Family income at 16yo	–0.003	0.005	0.523	–0.002	0.061	0.978
0|1				–0.070	0.485	
1|2				0.414	0.483	
2|3				0.953	0.501	
$\text{Residuals}_{HAPPINESS}$				0.286	0.208	0.168
Observations			2,919			
Weak instruments	*283.786*		*0.000****			

Wu-Hausman	*0.397*	*0.528*	
Sargan-Hansen	*0.123*	*0.726*	
Multiple R^2 or Pseudo R^2	*0.0221*		*0.0799*

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*
Robust standard errors were computed for both OLS models the Breusch-Pagan test indicated the presence of heteroskedasticity, violating the constant variance assumption of the error terms. Bootstrap standard errors with relative p-values were computed for the Ordered Probit model. The Variance Inflation Factor (VIF) test revealed no evidence of multicollinearity across the models.

2.9.2 Marginal effects

In interpreting marginal effects, only statistically significant variables are considered. As diagnostic tests indicated the absence of multicollinearity and interaction terms, the estimated marginal effects can be interpreted as distinct and not confounded by overlapping variance across predictors. The application of an instrumental variable strategy via the 2SRI approach allows for a causal interpretation of these results. By addressing potential endogeneity due to reverse causality and omitted variable bias, the IV strategy strengthens the inference that higher levels of subjective happiness causally reduce the likelihood of crack/cocaine use and drug injection.

Crack/cocaine use – Among all statistically significant variables, subjective happiness emerged as the most influential predictor of the probability of never having used crack/cocaine. As reported in Table 2.6, its marginal effect represents approximately 38.55% (ME = 0.0308, z = 1.99 at the "0" level of the outcome variable) of the total positive contribution of all predictors at the abstinence level of crack/cocaine, surpassing other well-established protective factors such as living with both parents at age 16 (31.67%), current family income (21.23%), and educational attainment (7.75%).

Drug injection – Similarly, subjective happiness was the strongest predictor associated with the probability of never having injected drugs. As reported in Table 2.7, its marginal effect accounts for approximately 69.16% (ME = 0.0257, z = 2.23 at the "0" level of the outcome variable), exceeding the contribution of current family income (20.10%) and educational attainment (9.70%).

The percentages reflect relative magnitudes of marginal effects at the abstinence level and should not be interpreted as variance explained.

These findings underscore the powerful and independent role of subjective happiness in reducing the likelihood of using these drugs, consistent with *social causation hypothesis*. Even after controlling for a wide range of cofounding factors – such as age, ethnicity, family background, and financial status – subjective happiness remains a robust protective factor. By applying the 2SRI model with instrumental variables, the study strengthens the causal interpretation of this relationship, demonstrating that higher happiness directly contributes to a lower risk of substance use.

In conclusion, these results provide empirical justification for including subjective happiness or emotional well-being as a central component of drug prevention strategies. Rather than relying exclusively on punitive measures and economic interventions, public health efforts should integrate initiatives that strengthen individual psychological well-being and resilience, foster meaningful social connections, and promote life satisfaction beyond material conditions.

More details about marginal effects are available in the Appendix (Table B.15, Table B.16).

Table 2.6: Marginal effects for level 0 – "Never drug use" before and after IVs estimations

	Crack/cocaine use			
	Before		After	
	ME	*z*	*ME*	*z*
Male	–.0145024	–1.92	–.0142689	–1.86
Age	.0005735	2.17	.0005723	1.94
Age^2	.0000652	4.15	.0000664	3.72
White	–.0028719	–0.20	–.002439	–0.16
Black	–.0105161	–0.61	–.0093445	–0.53
Hispanic	.0235788	1.67	.0216854	1.44
Years of education	.0062437	3.65	.0061983	3.61
Current family income	.0186329	4.22	.0169837	3.47
Subjective happiness	.016338	2.85	.0308401	1.99
Living in a small town at 16yo	–.0164163	–1.38	–.0175194	–1.41
Living in a large town at 16yo	–.0303626	–2.34	–.0308649	–2.26
Living in suburb at 16yo	–.0323505	–2.43	–.0321911	–2.45
Living in open country/on a farm at 16yo	–.0150286	–1.07	–.0159408	–1.16
Living with both parents at 16yo	.0270823	1.82	.0253373	1.75
Divorced or separated parents at 16yo	–.0113683	–0.71	–.0129651	–0.84
One or both parents died at 16yo	.0077519	0.36	.0043755	0.14
Family income at 16yo	–.00974	–2.28	–.0095616	–2.28

Abbreviations: ME, Marginal Effect; z, z-statistic

Table 2.7: Marginal effects for level 0 – "Never drug use" before and after IVs estimations

	Injection drug use			
	Before		After	
	ME	*z*	*ME*	*z*
Male	–.0014429	–0.25	–.0014481	–0.24
Age	.0003636	1.88	.0003667	1.79
Age^2	.00002	1.80	.000021	1.95
White	.0043046	0.42	.0044874	0.35
Black	.0190417	1.43	.0195143	1.19
Hispanic	.0264012	2.27	.0251741	1.43
Years of education	.003656	2.75	.0036004	2.51
Current family income	.0089762	2.63	.0074648	1.95
Subjective happiness	.0122615	2.70	.0256834	2.23
Living in a small town at 16yo	–.005539	–0.66	–.0060293	–0.67
Living in a large town at 16yo	–.0114745	–1.19	–.0114989	–1.12
Living in suburb at 16yo	–.0125141	–1.31	–.0119692	–1.16
Living in open country/on a farm at 16yo	.0313258	2.19	.0313438	0.82
Living with both parents at 16yo	.0143084	1.25	.0122819	0.98
Divorced or separated parents at 16yo	.0068642	0.55	.0053379	0.40
One or both parents died at 16yo	.0020539	0.13	–.0023007	–0.06
Family income at 16yo	–.0003011	–0.09	.0000953	0.03

Abbreviations: ME, Marginal Effect; z, z-statistic

2.10 Conclusion

This study examines the causal relationship between subjective happiness and high-risk substance use, focusing on crack/cocaine use and drug injection within the United States general population. Drawing on a large and representative sample from the General Social Survey (GSS), the study assesses the effects of subjective happiness on these high-risk behaviors, controlling for a comprehensive set of covariates, including demographic characteristics, socioeconomic conditions, stressful life events, and adverse experiences during adolescence.

The findings support both research hypotheses. First, subjective happiness emerges as a significant protective factor against use of substances. Individuals reporting higher levels of happiness are substantially less likely to engage in crack/cocaine use and drug injection across all models. Second, this relationship holds when tested for causality. By applying an instrumental variable approach with the 2SLS and 2SRI (Control Function), the study addresses potential endogeneity arising from reverse causality and omitted variable bias, thereby providing robust empirical evidence for causal interpretation. This strengthens the *social causation hypothesis*, which posits that positive psychosocial resources and experiences can reduce vulnerability to risky health behaviors, including substance use. While previous research often assumed a link between happiness and substance use, this analysis moves beyond correlation to demonstrate statistically credible evidence that higher levels of subjective happiness directly and significantly reduce the likelihood of engaging in substance use behaviors.

These results confirm not only statistical significance but also practical relevance. The marginal effects analysis reveal that subjective happiness is the most influential statistically significant factor in reducing the probability of substance use. It accounts for approximately 39% of the total protective effect against crack/cocaine use and nearly 70% in the case of drug injection. Overall, these findings reinforce the *social causation hypothesis*, suggesting that subjective happiness functions as a precursor influencing the likelihood of substance use. This reinforces the strategic value of subjective well-being in substance use prevention, even surpassing the effect of material factors such as income, which, while still relevant, plays a comparatively narrow influence.

In conclusion, the stronger protective association between subjective happiness and injection drug use, compared to crack/cocaine use, may reflect the escalating severity and risk associated with different stages of substance use behaviors. As individuals progress towards more hazardous practices like injection, the absence of protective factors, such as happiness, may have a more pronounced impact. In this sense, subjective well-being may serve as a buffer, especially at critical thresholds where the risk of physical harms and addiction escalates. Furthermore, since crack/cocaine use is a known precursor to injection drug use (Irwin *et al.*, 1996; Santibanez *et al.*, 2005; Ospina-Escobar & Magis-Rodríguez, 2022), happiness might also exert an indirect protective effect by reducing the likelihood of early-stage substance involvement, thus lowering the chances of progression to more dangerous substance behaviors.

2.11 Policy implications

This research carries important implications for both scientific understanding and the design of effective public health interventions. By establishing a causal relationship, it supports a more human-centered perspective in a field historically dominated by economic explanations and punitive and prohibitionist approaches. Rather than viewing substance use solely through the lens of material deprivation or behavioral deviance, other determinants such as subjective well-being, personal agency, a sense of belonging, and a purposeful life emerge as powerful protective factors. Political interventions that foster life satisfaction, individual and community emotional resilience, and social connectedness may therefore carry substantial benefits in reducing substance use, particularly in the early stages of experimentation, as highlighted in the marginal effect analysis.

Drug prevention strategies should be reframed as public health priorities, incorporating the promotion of happiness and well-being as protective factors at both national and community levels. They should not rely on punitive, prohibitionist, and ex-post measures such as incarceration or psychiatric hospitalization. For individuals at risk of substance use – or already engaged – policies enhancing subjective happiness should include school or community programs, workplace initiatives, and urban policies – especially in peripheral and disadvantaged areas – that strengthen social capital through inclusion, participation, civic engagement, and meaningful ties.

Policymakers should embrace an integrated and collaborative approach, ensuring greater coordination between social and public health institutions. Funding should prioritize drug prevention projects that identify and respond to evolving community needs, through the expansion of mental health services, the implementation of happiness-oriented programs in schools and youth centers, and community-based initiatives led by NGOs and civil society organizations. Such integrated efforts should bridge social policies, the healthcare system, and community organizations, fostering supportive environments that prioritize social capital, mental health, and overall well-being, ultimately reducing the risk of substance use.

In conclusion, while subjective happiness plays a significant role, it cannot be promoted in isolation. A comprehensive prevention strategy must adopt a multidimensional public health approach, also addressing economic insecurity, educational disadvantage, and family instability. Recognizing subjective happiness as a central pillar of prevention is not just important, it is foundational to any strategy that seeks to address substance use through the lens of dignity, resilience, and long-term well-being.

2.12 Limitations

A first limitation concerns the distribution of the dependent variables. Given the low prevalence of drug use in the general population, some response categories contained only a few observations, raising potential concerns about unstable estimates. To address this issue, categories were partially collapsed to improve model stability while preserving the substantive interpretation of results.

A second limitation is the cross-sectional structure of the dataset that limits causal inference over time, since no panel data is available to perform longitudinal investigation. Additionally, variables such as parental substance use, attendance in recovery programs, drug policy exposure, and the use of other psychotropic substances were not included, thereby narrowing the scope of the analysis.

Despite the large number of observations, the presence of missing values led to the removal of important cases, reducing the sample size and the number of usable variables. The handling of missing values reduced the sample size, largely due to the inclusion of key retrospective covariates and instrumental variables, which were necessary to capture early-life risk factors and address potential endogeneity. While these choices inevitably reduced the number of usable cases, they ensured theoretical consistency and greater robustness of the empirical models.

Future research should examine specific population subgroups, emerging patterns of substance use, and the effectiveness of targeted policy interventions for high-risk behaviors.

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Chapter 3

3. Does forest cover loss undermine institutional trust? A cross-country analysis from Latin America and the Caribbean (2008–2023)

Abstract

Forest cover loss is a critical environmental issue in Latin America and the Caribbean (LAC), driven by agricultural expansion, mining, urbanization, and deforestation. Beyond its ecological consequences, it may also undermine social and political stability. This study examines the impact of forest cover loss on citizens' trust in public institutions, defined as confidence in the fairness, competence, and integrity of governments, parliaments, courts, and political parties. Using a macro-panel dataset combining AmericasBarometer survey data with geospatial tree cover loss metrics from Global Forest Watch (2008–2023), the lagged fixed effects analysis shows that general forest cover loss ($\beta = -0.0275$, $p < 0.001$) and losses in critical biomes ($\beta = -0.0225$, $p = 0.003$) are significantly associated with lower institutional trust. Results hold when distinguishing between short-term within-country losses and long-term structural degradation across countries, both are consistently linked to declining trust. Models also account for key controls such as GDP, democracy quality, urbanization, and corruption, which confirm their expected associations. These findings contribute to the literature on the societal consequences of environmental degradation, revealing that forest cover loss is not only an ecological emergency but also a pressing social concern that must be tackled to preserve institutional legitimacy across the LAC region.

3.1 Introduction

The world's forest areas cover 4.06 billion hectares, or approximately 31% of the world's land surface. Forests play a critical role in sustaining biodiversity, regulating the climate, and providing livelihoods. They support vital ecosystem services such as carbon dioxide absorption, hydrological cycle regulation, soil protection, and the provision of timber, food, medicine, and fiber. As of 2020, natural forests accounted for 97.7% of global forest area, with plantations covering the remaining 2.3% (ECLAC, 2021).

However, forests face increasing threats from human activates, fires, unsustainable land and water use, logging, and pollution. These factors contribute to widespread forest degradation, jeopardizing biodiversity, ecosystem stability, and human well-being. Indeed, the most detrimental effects of deforestation include increased surface run-off leading to floods and landslides, rising local temperatures that turn some tropical forests from carbon sinks into carbon sources, greater human exposure to disease vectors, and deteriorating air quality due to the loss of forests' natural filtering capacity (Almeida *et al.*, 2024).

The collapse of key ecosystem services – such as pollination, marine food provision, and native timber supply – could lead to an estimated global GDP loss of $2.7 trillion annually by 2030. This vulnerability is particularly acute in low-income countries, where economic are more directly dependent on nature (World Bank, 2021).

Latin American and the Caribbean (LAC) are home to 50% of the world's tropical forests and 40% of its biological diversity. The region hosts 11 of the 14 terrestrial biomes, the second-largest reef system globally, and a third of global freshwater resources. However, between 1990 and 2005, forest cover loss was severe, with nearly 69 million hectares lost – approximately 7% of its total forest cover. While global deforestation averaged 0.1% per year, South America alone lost 0.4% annually (OECD, 2018).

Currently, 38% of the Amazon forest is affected by degradation through fires, edge effects, logging, and drought. These processes drastically reduce dry-season evapotranspiration, accelerate biodiversity loss, and strain forest-dependent communities (Lapola *et al.*, 2023). Flores *et al.* (2024) warn that up to and 47% of Amazonian forests could face overlapping ecological disturbances by 2050, potentially provoking abrupt ecological transitions and intensifying regional climate change, with some areas projected to warm by over 4 °C.

In this context, forest cover loss is no longer solely an environmental issue, it becomes also a societal and political concern. Public institutions should play a key role in safeguarding natural ecosystems, and their ability to do so is increasingly evaluated through the lens of public trust. Like health or human rights, forest protection demands institutional commitment, transparency, and accountability. Yet in LAC, trust in public institutions is fragile and declining, shaped by electoral volatility, economic inequality, personalized politics, and widespread perceptions of corruption (Ross & Escobar-Lemmon, 2011; Baccini *et al.*, 2025). Therefore, trust is highly sensitive to perceived government performance and is closely linked to the delivery of public goods and social policies (Cáceres, 2019; Surillo, 2023).

This paper investigates the relationship between forest cover loss and trust in public institutions across LAC countries from 2008 to 2023. By harmonizing geospatial and survey measures of institutional trust, it constructs a comprehensive dataset to estimate the fixed effects of forest cover loss on aggregate trust and its disaggregated dimensions (i.e., trust in the president, congress, political parties, elections, police, and the army). This cross-country study is the first empirical attempt to directly assess whether forest degradation erodes institutional trust, linking ecological disruption with governance, institutional legitimacy, and democratic stability. It is also conceptually grounded in the *associationist model* of trust, which interprets institutional trust as an outcome of collective experiences and perceived performance rather than a precondition for cooperation. In this paper, the terms *tree cover loss* and *forest cover loss* are used interchangeably.

The structure of this paper begins with a theoretical grounding, followed by the empirical investigation. The next section presents the research question and the hypotheses guiding the analysis. Subsequent sections describe the data sources and variables used, provide descriptive statistics, and outlined the methodological approach. The results are then presented, along with robustness checks to test the stability of the findings. Finally, the concluding section discusses policy implications and limitations of the study.

The analysis was conducted using Stata.

3.2 Theoretical framework

This section outlines the theoretical framework by defining trust in public institutions and examining its core dimensions. It then reviews the main theoretical perspectives on institutional trust in Latin America and the Caribbean. Lastly, it presents a contextual overview of forest cover loss in that geographical region.

3.2.1 Trust in public institutions

Trust in public institutions is commonly understood as a specific form of vertical trust, where individuals believe that institutions are competent, fulfil their obligations, and act responsibly. It is integral to broader evaluations of democracy and includes both trust in the *public system* (i.e., parliaments, governments, courts) and in *public actors* including politicians, political parties, and heads of state (Sapienza, 2021). This type of trust is based on citizens' evaluations of institutions' capacity to govern effectively, pursue legitimate goals, and demonstrate the competence needed to achieve them.

This relationship is shaped by multiple layers of trust: personal trust towards politicians, institutional trust towards the roles and histories of public bodies, and political trust aligned with ideological preferences or party affiliations (Badman *et al.*, 2022). Trust grows or weakens as citizens experience the outcomes of political leadership and institutional performance over time. Additionally, trust implies confidence that institutions are reliable, effective, and committed to the public good. As Easton (1975) argued, trust reflects not just people's satisfaction with results, but with the perceived fairness, transparency, and stability of the process that produce them. Keefer & Scartascini (2022) explained that institutions are essential for enabling citizens to hold governments accountable, thereby helping to build trust. When functioning properly, judiciaries and legislatures act as checks on executive power, curbing opportunistic behavior. Political parties can also serve as channels for collective citizen action, but, when institutions lose credibility, they may become part of the problem, further deepening public distrust.

Two main theoretical perspectives help explain how trust in public institutions develops: the *political culture approach* and the *institutional or constitutional approach* (Perry, 1976). The political culture approach views political trust as exogenous, shaped by long-standing cultural norms and early-life socialization. From this perspective, political trust stems from general social trust: if most people in a society are considered trustworthy, then institutions composed of these individuals are also seen as trustworthy (Jackman & Miller, 1996; Foley & Edwards, 1999; Kaasa & Andriani, 2022).

By contrast, the institutional approach sees trust as politically endogenous, as a result of how well institutions practically perform. Citizens assess institutions based on their political and economic outcomes, rewarding competence and integrity with trust, or penalizing failure with skepticism (Dasgupta, 1988; Hetherington, 1998). The line of thinking – grounded in Locke's philosophy – also emphasizes the importance of check and accountability mechanisms, treating some degree of distrust as necessary for democratic balance (Perry, 1976). Although these perspectives differ, they are not mutually exclusive. Institutional performance can interact with cultural predispositions, complicating attempts to isolate their effects. Nonetheless, the institutional perspective has gained strong support since trust levels shifted significantly in response to political performance and leadership changes.

As Mishler & Rose (2001) demonstrate in post-Communist countries, trust in institutions is largely shaped by how individuals interpret their lived experiences with political and economic systems. Contrary to cultural perspectives, social and interpersonal trust do not automatically translate into trust in institutions. In Communist regimes, for example, close personal ties often formed in opposition to formal institutions, which were perceived as coercive and unaccountable. Consequently, personal and political trust remained separated.

These findings allude to the fact that trust does not require generations to build, as cultural theories indicate. It can grow when institutions respond to citizens' needs, combat corruption, and protect freedoms. Conversely, poor institutional performance can rapidly erode trust. In this sense, trust is less a cultural inheritance than a reflection of how well institutions function in citizens' eyes. According to Easton (1975), trust in institutions is not only linked to economic sphere, such as investments or growth, but also to legitimacy, which encompasses policy making, policy implementation, and the delivery of the stage services that sustain peaceful transitions of power and reduce regime volatility.

Ringeling (1993) identified four criteria commonly used by citizens to evaluate institutions and their performance: (*i*) an *instrumental criterion* referring to effectiveness and efficiency, (*ii*) a *bureaucratic criterion* assessing legality and procedural fairness, (*iii*) a *contingency criterion* addressing responsiveness and representativeness, and (*iv*) a *symbolic criterion* reflecting alignment with societal values. These criteria vary across contexts and over time, shaped by individual expectations and social environments. Moreover, evaluations of institutional performance generally follow two theoretical models. (*i*) The *macro-performance theory* links changes in trust across countries and over time to broad indicators such as economic growth, inflation, unemployment, and political stability. (*ii*) The *micro-performance theory* underlines citizens' perceptions of how efficiently institutions function, how politicians behave, and how public services are delivered (Bouckaert & Van de Walle, 2002).

However, there are persistent doubts about whether performance alone can explain levels of political trust. A central issue is how citizens perceive institutional effectiveness. Even when institutions perform well by objective standards, trust may not increase if public perception fails to align with those improvements. This disconnect can stem from limited access to accurate information, entrenched biases, or generalized skepticism. Citizens' judgments are often selective, shaped by personal expectations, past experiences, and broader sociopolitical contexts (Bouckaert & Van de Walle, 2002). In this regard, the information environment plays a crucial role. While both traditional and social media are key channels for disseminating information, they can also act as echo chambers, amplifying misinformation and further widening the gap between actual performance and perceived legitimacy (Sapienza, 2021). Therefore, fostering institutional trust requires not only effective governance but also clear, transparent, and responsive communication. As Alfano & Huijts (2020) emphasized, information should be timely, honest, and tailored to public concerns, not merely what institutions think the public should know. A credible and open information strategy is essential for enhancing institutional legitimacy and building lasting trust.

3.2.2 Institutional trust in Latin America and the Caribbean

Over the past decades, Latin America and Caribbean (LAC) have witnessed a steady decline in trust in political institutions. As outlined in this section, trust in political institutions has been shaped not only by cultural and institutional factors but also by the interaction between electoral systems and economic conditions.

Drawing on data from eleven Latin American countries between 1996 and 2006, Ross & Escobar-Lemmon (2011) showed that countries with personalizing electoral systems, where voters focus on individual candidates, experience greater volatility in political trust during periods of economic downturn. In contrast, partyizing systems, which draw attention to party accountability, tend to maintain more stable levels of institutional trust regardless of economic performance. While personalizing systems can strengthen ties between voters and their representatives, they also make institutional trust more sensitive to economic shocks. For example, the contrast between Colombia and Venezuela illustrates how political trust erodes more rapidly in systems with highly personalized accountability when the economy weakens. Although party-based systems may seem less responsive to individual concerns, they provide a stabilizing effect in times of crisis. This reveals a key institutional trade-off in Latin America. While personalizing politics may enhance perceived political responsiveness, it can come at the cost of institutional resilience. In politically and economically fragile democracies, such electoral designs may deepen public distrust during difficult times.

Furthermore, data from Latinobarometro (2009–2018) indicates that by 2018, only about 20% of the population expressed trust in their governments. This trend reflects deep-rooted structural issues such as exclusion, inequality, weak state capacity, and widespread perceptions of corruption, that have long undermined the legitimacy of political institutions in the LAC area (Baccini *et al.*, 2025). Corruption, in particular, reinforces the belief that institutions serve elites rather than the public, further eroding confidence in governance.

Trust levels, however, have not been uniform across the region and have fluctuated in response to political and social development. Between 2018 and 2020, some countries – such as El Salvador, Uruguay, the Dominican Republic, Mexico, Brazil, and Colombia – experienced renewed trust in government, possibly driven by the election of political outsiders who broke from traditional party systems and, in some cases, by effective responses to the COVID-19 pandemic (UNDP, 2024).

Despite these fluctuations, confidence in national legislatures has remained low, depending on how effectively and responsibly leaders are perceived to govern.

Levitt (2011), for example, identified Peru as a case where trust in Congress declined even as the institution gained greater autonomy. His concept of the “legislative autonomy gap” indicates that trust is closely tied to public expectations: citizens tend to distrust legislatures not necessarily because they are too powerful or too weak, but because they fail to align with what people expect them to be. Surillo (2023), using data from 2021, highlighted that trust in government across LAC is strongly associated with citizens’ evaluation of executive performance. Presidential job approval emerged as the strongest predictor of government trust, surpassing respect for institutions, perceptions of personal economic well-being, or beliefs about the protection of basic rights. Trust also varied by socio-demographic factors: older citizens tended to trust more, while those with higher education and wealth reported lower levels of trust, possibly due to elevated expectations and political awareness. The report also illustrates how trust may rise with visible, short-term benefits, as in the case of El Salvador under President Bukele, where strict public security and pandemic measures led to increased public support. However, this may risk prioritizing popularity over long-term democratic governance.

Nevertheless, research also reported that trust can increase when governments are seen as effectively addressing social needs.

Cáceres (2019) argued that left-leaning governments have often garnered more trust due to their focus on poverty reduction and redistributive policies. Such trust tends to be transactional rather than ideological, rooted in perceptions of improved well-being. However, when governments fail to deliver public goods – often due to fiscal constraints – trust diminishes. Similarly, Baccini *et al.* (2025) suggested that left-wing populist leaders, such as Evo Morales and Rafael Correa, restored trust among excluded groups by emphasizing inclusion, social justice, and anti-elite rhetoric. Their credibility derived less from ideology than from addressing the concrete needs of the population. Parra Saiani *et al.* (2021) further underlined that political trust in the region is highly sensitive to crises and changes. Their analysis of 18 countries between 2008 and 2018 shows that trust often declined during episodes of corruption, authoritarianism, or economic uncertainty – as in Brazil, Mexico, Peru, and Nicaragua in 2017–2018. By contrast, countries with stronger rule of law, such as Uruguay, Costa Rica, and Chile, maintained higher levels of trust. Yet even in these contexts, as in Chile during the 2019–2020 demonstrations, civic unrest did not necessarily signal a breakdown of trust in democratic institutions. Rather, such mobilizations reflected active demands for greater inclusion, equity, and institutional responsiveness, particularly from marginalized groups.

3.2.3 Forest cover loss in Latin America and the Caribbean

Over the past 30 years, LAC have experienced a significant decline in natural forest cover. Between 1990 and 2020, the region's forest area fell from 1.07 billion hectares (ha) to 932 million ha, shrinking from 53% to 46% of total land area. This loss of 138 million ha – equivalent to the entire territory of Peru or half of Argentina – primarily affected natural forests. By contrast, plantation forests expanded by only 14 million ha, a growth insufficient to compensate for the overall decline (ECLAC, 2021).

The pattern of forest cover loss varies across the region. Brazil, which holds 53.3% of LAC's forests, lost over 92 million ha during this period. Other major contributors include Bolivia (7 million ha), Argentina (6.6 million ha), Colombia (5.8 million ha), and Paraguay (9.4 million ha). Smaller countries experienced higher proportional losses, with deforestation rates exceeding 20% in Nicaragua, Guatemala, Paraguay, and Honduras. By contrast, ten countries – including Chile, Costa Rica, Uruguay, and the Dominican Republic – reported gains in forest cover. However, these gains represent only 5.2% of the region's total forest area and do not counterbalance the regional trend of decline (ECLAC, 2021).

Recent trends in Latin America reveal an alarming acceleration of tropical primary forest cover loss, with several countries experiencing record-breaking rates in 2024. Brazil accounted for over 40% of global tropical primary forest cover loss. The amazon biome alone saw a 110% increase from the previous year, with 60% of this loss driven by fires. The Pantanal – Brazil's vast tropical wetland – also suffered significant deforestation. Bolivia recorded a 200% increase in primary forest cover loss, ranking second globally. Fires set for agricultural expansion, especially soya and cattle, spiraled out of control amid severe droughts. In Guatemala, illegal ranching and settlement expansion, also in protected areas, drove widespread deforestation. Mexico nearly doubled its forest cover loss, particularly in Campeche and Quintana Roo. Nicaragua recorded the highest relative forest cover loss in 2024 (4.7%), mainly in Indigenous territories. Peru experienced a 135% increase in fire-related forest cover loss, and Guyana recorded a fourfold increase (GFR, 2025).

The main drivers of forest decline in LAC are land conversion for agriculture, livestock, and commercial forestry. This transformation is linked to rapid economic and population growth: between 1990 and 2010, the region's GDP rose by 87%, and its population grew by over 30% (OECD, 2018). Export-oriented commodities like soy, biofuels, and livestock remain the most significant cause of deforestation, with over 90% of forest cover loss in Brazil's Cerrado and the Peruvian Amazon is linked to agricultural expansion. Illegal logging, unregulated mining, and illicit crop cultivation further degrade forests, especially in Colombia and Peru, exacerbated by weak land tenure systems and poor enforcement (OECD, 2018). According to Carter *et al.* (2018), Latin America had the highest share of agriculture-driven deforestation globally (78%) and the highest associated emissions, peaking at 974 ± 148 Mt CO_2 per year in the early 2000s.

Infrastructure and urban development also contribute significantly to deforestation. Road and highways have opened remote forest areas to clearing, particularly in Colombia and Brazil, where many are built without adequate environmental planning. Mining, hydroelectric projects, and pipelines disrupt ecosystems and drive land-use change. Sonter *et al.* (2017) estimated that between 2005 and 2015, mining caused 11,670 km² of deforestation in Brazil's Amazon – twelve times the forest cover loss within official mining leases.

Finally, forest fires are another growing threat, often linked to land-use change or mismanagement, especially in Chile and Brazil. Broader environmental pressures – including desertification, overgrazing, water overuse, and climate-driven droughts – affect drylands in northeastern Brazil, the Andean highlands, and parts of Argentina and Chile. Up to 50% of agricultural land in LAC may be at risk of desertification by 2050 (OECD, 2018).

3.3 Literature review

Although the nexus between environmental degradation and trust in public institutions has received growing attention, much remains unknown about how specific forms of degradation, such as forest cover loss, affect public confidence in institutions. This section reviews key findings from the existing literature on environmental degradation and forest cover loss.

3.3.1 Environmental degradation and institutional trust

The relationship between environmental degradation and trust in public institutions has gained attention in recent literature, though direct evidence from LAC remains limited. Studies generally propose a two-way relationship: (*i*) environmental harm and weak crisis management can erode public trust, while (*ii*) trust in institutions is also necessary for effective environmental governance.

Empirical evidence from China reveals that higher levels of both measured and perceived environmental pollution are associated with lower trust in local and national governments (Gong *et al.*, 2017; Chen & You, 2021; Yao *et al.*, 2022; Ruan *et al.*, 2022). This erosion is especially pronounced among environmentally concerned individuals, indicating that poor environmental governance can undermine political legitimacy, even when it is rooted in economic growth. However, governments that respond actively and credibly to environmental issues can partially restore public trust. Flatø (2022) further found that poor air quality reduces trust in local and provincial governments in China, while trust in the central government remains relatively stable. These findings suggest that local environmental failures can have broader implications for political stability. At the macro level, Mingo & Faggiano (2020) argued that institutional trust acts as a form of public evaluation: citizens reward governments that manage crises well and penalize those that fail to do so or exacerbate inequality.

Among the multiple dimensions through institutions are evaluated, environmental crises management emerges as a key factor influencing public trust. Schroeder *et al.* (2025) showed that low political trust undermines international climate negotiations, while Buntaine (2025) argued that inadequate responses to climate disasters weaken confidence in public institutions, particularly in fragile states. Mackay *et al.* (2023), analyzing data from over 1,000 disaster events and nearly 89,000 individuals across 36 African countries, found that experiencing natural disasters during early adulthood (ages 18-25) has long-term effects on interpersonal and institutional trust. In particular, those exposed to such disasters are less likely to trust political institutions like the president and electoral commissions. In Mexico City, people who trust the government are more willing to support environmental taxation and policy (Hoffmann *et al.*, 2022). In Ecuador, political distrust is linked to greater concern about climate risks (Verner, 2023). Similarly, in sub-Saharan Africa, climate awareness often correlates with institutional distrust, especially in regions marked by inequality and conflict (Dirksmeier *et al.*, 2023). Another study from the same region demonstrated that climate disasters such as droughts, floods, storms, and extreme temperatures reduce citizens' trust in public institutions and, in turn, their willingness to pay taxes. However, when institutions are perceived to respond fairly and effectively, trust can be preserved or even strengthened (Nicoletti & Tagem, 2025).

Trust also plays a critical role in environmental engagement. Studies indicate that trust in institutions and key actors supports public acceptance of environmental policies and promotes pro-environmental behavior (Cologna & Siegrist, 2020; Bronfman *et al.*, 2008; Duradoni *et al.*, 2025). Where governments express skepticism about climate change, public commitment to environmental action tends to weaken. Conversely, trust in local, regional, and national administrations increases support for environmental policies, particularly among individuals who are less concerned about climate issues (Levis & Smith, 2024). Additional evidence supports that trust shapes not only attitudes but also deeper behavioral patterns. Deák *et al.* (2024), analyzing Central and Eastern Europe, found that personal and institutional trust are linked to stronger climate norms and a heightened sense of personal responsibility. Arnone *et al.* (2025) observed a similar pattern in Italy: in regions with higher political trust, Environmental, Social, and Governance (ESG) initiatives are more effectively implemented, and successful ESG practices can, in turn, strengthen political trust. Kulin & Sevä (2020) further added that trust in impartial institutions – such as courts and police – is a stronger predictor of support for environmental policies than trust in partial institutions, such as elected officials. People are more likely to back demanding measures like carbon taxes when they believe enforcement institutions are fair and reliable.

Finally, the impact of natural resource extraction is closely linked to debates on the "resource curse", which supports the view that natural wealth can weaken governance and public trust (Alssadek & Benhin, 2023). Mavisakalyan & Minasyan (2022), using survey data from over 43,000 individuals across 27 post-communist countries, found that people living near active mining sites tend to have lower trust in government than those near inactive mines. This mistrust is largely driven by perceptions of corruption and poor public service delivery, and it appears to weaken civic engagement and willingness to protest. By contrast, Miller (2015) reported the opposite in four democratic African countries, where residents of mining districts expressed higher political trust than those in non-mining areas. This increase appears to be linked to the economic benefits that resource extraction brings to local communities.

3.3.2 Forest cover loss and institutional trust

The relationship between forest cover loss and trust in public institutions remains largely underexplored in the academic literature. As outlined in the previous section, a growing body of research links environmental degradation to political trust. Most studies have focused on extractive industries such as oil and mining (Miller, 2015; Mavisakalyan & Minasyan, 2022), the political repercussions of environmental pollution (Ruan *et al.*, 2022), and the lasting effects of natural disasters on social cohesion and confidence in government (Mackay *et al.*, 2023). Although forest loss is rarely addressed directly, these works provide useful insights into the potential mechanisms at play.

Evidence from disaster-prone contexts present the sensitivity of trust to environmental crises. In Chile, public trust in government authorities and disaster response agencies is consistently low in relation to hazards such as earthquakes, tsunamis, and wildfires (Bronfman *et al.*, 2016). In California, perceptions of wildfire risk and support for mitigation policies are strongly influenced by personal experience, institutional trust, and socio-demographic factors (Masri *et al.*, 2023). At a broader level, cross-country data indicate that stronger institutions and lower levels of corruption are associated with lower rates of deforestation (Moreira-Dantas & M. Söder, 2022).

Research specifically focused on wildfires offers further evidence. Adamis & Papanikolaou (2011) and Papanikolaou *et al.* (2012) examined the social consequences of a major wildfire in rural Greece. Despite the country's historically low levels of public confidence in institutions, both disaster victims and non-victims reported distrust across nearly all institutions, including government, the military, media, and the church. Yet victims displayed significantly higher hostility and lower trust levels in the aftermath of the disaster. The authors argue that in contexts with weak baseline trust and cohesion, environmental shocks can exacerbate social fragmentation and deepen institutional distrust.

Complementary evidence comes from forest governance studies. Murtazashvili *et al.* (2019), while not directly analyzing trust in public institutions, found that higher levels of interpersonal trust are correlated with lower rates of deforestation across countries, even when controlling for democracy and economic development. Their findings stress the importance of social capital for collective action in environmental management, suggesting that local participation in forest governance can simultaneously promote conservation outcomes and strengthen community trust.

This literature points that while direct analyses of forest cover loss and institutional trust are scarce, related evidence points a dual dynamic: (*i*) environmental degradation can erode confidence in public institutions, while (*ii*) higher levels of trust – whether interpersonal or institutional – can facilitate more effective governance of natural resources. This reciprocal relationship is central to understand how forest loss may interact with institutional trust in the LAC region.

3.4 Research question

This paper investigates whether forest cover loss influences citizens' trust in public institutions across Latin American and the Caribbean (LAC) countries between 2008 and 2023. Forest cover loss in the region is primarily driven by human activates such as agricultural expansion, mining, logging, infrastructure, and uncontrolled fires, making LAC responsible for nearly 60% of global forest cover loss (FAO, 2020; Ritchie, 2021). Beyond their ecological value, forests are essential for biodiversity, climate regulation, and human well-being, placing forest governance at the center of environmental and political debates.

Institutional trust refers to citizens' confidence that governments, courts, parliaments, and political actors act competently and fairly in pursuit of the public good (Easton, 1975; Sapienza, 2021; Keefer & Scartascini, 2022). While cultural perspectives emphasize inherited norms (Jackman &

Miller, 1996; Foley & Edwards, 1999), performance-based approaches underline how public trust responds to institutional effectiveness and responsiveness (Hetherington, 1998; Mishler & Rose, 2001; Bouckaert *et al.*, 2002). In LAC, where trust remains fragile, performance failures and unmet expectations have shaped skepticism toward public institutions, though effective social policies and inclusive leadership have at times restored confidence (Ross & Escobar-Lemmon, 2011; Levitt, 2011; Cáceres, 2019; Parra Saiani *et al.*, 2021; Baccini *et al.*, 2025).

The link between forest cover loss and institutional trust remains largely underexplored. Existing research mainly connects environmental degradation to political trust through cases of pollution (Ruan *et al.*, 2022), natural disasters (Mackay *et al.*, 2023), or extractive industries (Miller, 2015; Mavisakalyan & Minasyan, 2022). These studies demonstrate that environmental crises can erode confidence in government, especially when institutions are seen as unresponsive or corrupt. Evidence from China, California, and Greece indicates that weak disaster responses or wildfires reduce trust and increase hostility toward institutions (Bronfman *et al.*, 2016; Masri *et al.*, 2023; Adamis & Papanikolaou, 2011; Papanikolaou *et al.*, 2012).

However, few studies directly assess how forest cover loss itself affects institutional trust. Murtazashvili *et al.* (2019) provide partial insights by showing that higher interpersonal trust reduces deforestation through stronger collective action, but their focus is on governance outcomes rather than citizens' trust in institutions. This leaves a gap in understanding whether citizens perceive forest cover loss as a failure of institutional performance and legitimacy, particularly in democratic contexts.

This research aims to address that gap by analyzing the causal impact of forest cover loss on institutional trust in the LAC region. Drawing on harmonized survey data and high-resolution geospatial tree loss metrics, this study provides the first large-N, cross-country analysis of the political consequences of forest cover loss in the LAC region. Given the potential bidirectionality of the relationship – with forest loss potentially eroding institutional trust but trust itself facilitating or hindering environmental governance – the empirical design explicitly addresses risks of reverse causality. By exploiting panel data with country- and year-fixed effects, the analysis isolates the within-country variation over time, allowing identification of the effect from forest cover loss to institutional trust. In doing so, it offers new empirical evidence on how environmental degradation shapes public perceptions of governance in a region where forest conservation remains a politically sensitive and globally significant challenge. Moreover, unlike previous works, this research examines institutional trust in both aggregate and disaggregate form, distinguishing between *political leadership* (e.g., the president, congress, political parties), *democratic mechanisms* (elections), *local government* (municipality), and *law enforcement institutions* (police and the army). This dual approach makes it possible to assess whether the erosion of trust is selective, depending on an institution's role and its perceived responsibility for environmental management.

In this context, two main hypotheses guide the empirical analysis:

H1: Forest cover loss reduces citizens' trust in political institutions. As forests diminish, citizens may perceive this as a governance failure, lowering trust in institutions responsible for safeguarding public goods and ensuring environmental sustainability.

H2: The effect of forest cover loss on institutional trust varies across types of public authorities. Institutions directly involved in policy-making and environmental management (e.g., the president, congress, political parties, and municipality) are expected to experience a greater decline in public trust than institutions perceived as less directly responsible, such as law enforcement or electoral bodies.

Understanding this relationship is crucial for contemporary environmental governance. Forests are vital for sustainability, and their loss has political consequences extend beyond ecology. It shapes how citizens evaluate state effectiveness and legitimacy, reflecting broader expectations that governments must protect common goods. When institutions fail, trust erodes and perceptions of neglect or mismanagement grow. Conversely, effective forest conservation can enhance legitimacy and public support for environmental action. Thus, responses to forest cover loss are not only environmental issues but also matters of governance quality, citizen trust, and democratic stability.

3.5 Data and variables

To conduct a cross-country analysis, a panel data was constructed by merging multiple sources, incorporating measures of institutional trust, forest cover loss, and several covariates used as model controls. The final dataset comprises 204,243 observations, with institutional trust data drawn from the LAPOP Lab's *AmericasBarometer* – one of the leading public opinion surveys in the Americas. The *AmericasBarometer* provides systematic insights into the region's political, social, and economic landscapes, relying on rigorous methodology and comprehensive coverage across Latina America and the Caribbean. Its common core questionnaire and standardized procedures ensure comparability across countries and over time.

The database also includes sampling weights and stratification data, which allow for appropriate cross-country comparisons. These are applied using survey design commands, following the technical guidelines provided to ensure representativeness and comparability of estimates across the selected countries and years. Further details are discussed in the section on methodology.

3.5.1 Institutional trust indicators

To measure institutional trust, seven variables were selected to maximize country and years coverage: trust in the president, congress, political parties, elections, municipality, police, and the army. Together, these variables provide a reliable measure of confidence in key public institutions from 2008 to 2023, across a wide set of LAC countries, including Argentina, Bolivia, Brazil, Chile, Colombia, Dominican Republic, Ecuador, El Salvador, Guatemala, Guyana, Honduras, Jamaica, Mexico, Nicaragua, Paraguay, Peru, Uruguay, and Venezuela. Each trust item is measured on a 7-points Likert scale, where 1 corresponds to "*No trust at all*" and 7 to "*A lot of trust*".

3.5.2 Forest cover loss indicators

To study forest cover loss, this research uses tree cover data produced by the Global Land Analysis & Discovery (GLAD) laboratory at the University of Maryland, in partnership with Google. These data are made publicly available through the Global Forest Watch (GFW) platform, which provides annual estimates of tree cover loss and associated carbon emissions from 2001-2023. The data are derived from geospatial analysis and satellite imagery. In line with the Global Forest Change dataset, tree cover loss is defined as "stand replacement disturbance", indicating the removal of at least 50% of tree canopy within a 30-meter pixel (Hansen *et al.*, 2013; Potapov *et al.* 2022).

GFW provides tree cover statistics based on varying canopy cover thresholds, including >10%, 15%, 20%, 25%, 30%, 50%, and 75% canopy density levels, measured as of the year 2000. While GFW typically adopts a >30% canopy cover threshold as the default, users are advised to select the desired canopy cover level based on their specific analytical needs and apply it consistently throughout their analyses (GFW, 2024; GFR, 2025).

In this research, two measures of forest cover loss were considered: (*i*) a general forest cover loss, defined as annual tree cover loss in areas with an initial canopy cover of ≥10%; and (*ii*) specific forest cover loss, focusing on more densely forested areas with thresholds of ≥50% and ≥70% canopy cover. Tree cover refers to all vegetation greater than five meters in height, and "loss" indicates any reduction due to human activities such as logging, agriculture, and urban expansion, as well as natural causes like wildfires, storms, and disease (GFW, 2025).

General forest loss was calculated as the annual tree cover loss (≥10% canopy cover) in hectares, divided by the total baseline tree cover extent (≥10% canopy cover) in 2000 for each country. Similarly, specific forest loss was computed as the annual tree cover loss in critical biomes (≥50% and ≥70% canopy cover), normalized by the corresponding 2000 baseline extent. This normalization ensures that all yearly values represent the proportion of forest lost relative to the initial forest stock, allowing for comparability across countries and over time by avoiding distortions that would arise from annually declining denominators.

3.5.3 Control variables

To isolate the impact of forest cover loss on institutional trust, the model includes a set of selected covariates based on established literature. Specifically, the analysis controls for factors commonly associated with institutional trust: democratic quality, economic development, and perceptions of corruption, alongside a measure of urbanization.

Democracy is conceptualized as a political system grounded in free and fair elections, collective decision-making, political equality, and the free formation of public opinion (Beetham, 1994). To capture this dimension, the analysis employs the Democracy index developed by the Economist Intelligence Unit (2006-2024), which aggregates indicators of electoral processes, civil liberties, political participation, preference for democracy, and government functioning. The index ranges from 0 to 10, with higher scores indicating greater democratic consolidation.

Economic development is another component usually linked to higher levels of political trust, both within and across countries (Bienstman, 2023). In this analysis, GDP per capita – current prices in US dollars – is employed as a standard measure of economic prosperity, capturing national income levels and economic growth. Studies showed that countries with higher GDP per capita tend to report greater trust in political institutions (Kołczyńska, 2020). Data on GDP per capita were sourced from the United Nations Statistics Division.

Closely related to democracy is the issue of corruption, widely recognized as key driver of eroding institutional trust (Boly & Gillanders, 2022). For this study, the Corruption Perceptions Index developed since 1995 by Transparency International was utilized. The CPI reflects experts and business leader assessments of public sector corruption, specifically the abuse of public power for private benefit. The CPI is coded such that higher values indicate lower perceived corruption. Empirical studies have demonstrated erosive effects of corruption on institutional trust, not only at a general level but also targeting specific institutions. For instance, Beesley & Hawkins (2022) revealed significant negative impacts of corruption on trust in political parties (-0.317), congress (-0.167), the legal system (-0.201), and the criminal justice system (-0.181) in Peru.

Lastly, the urbanization rate is included to control for differences between urban and rural populations. Urban and rural residents may perceive environmental degradation and government performance differently, which could confound the relationship between forest cover loss and institutional trust. The urbanization rate measures the proportion of a country's population living in areas classified as urban, based on definitions provided by national statistical agencies and harmonized by the United Nations Population Division via the World Bank.

3.6 Descriptive statistics

Descriptive statistics summarize country-level averages for institutional trust and key structural indicators across 17 LAC countries from 2008 to 2023. The data reveal substantial variation in trust across institutional domains and between countries, reflecting heterogeneity of the region in terms of institutional perceptions, structural conditions, and environmental degradation. Including a broad set of countries offers a more comprehensive view of these regional dynamics.

As shown in Table C.1 in the Appendix, average trust in the army (T-1) is higher than trust in congress (T-3) and political parties (T-5), which receive the lowest mean scores. This pattern reflects a general trend coherent with existing literature, which observes higher public confidence in security-related institutions and lower trust in political ones (Kavanagh *et al.*, 2020).

Country differences are also evident. Uruguay reports the highest mean trust in elections (T-2), while Brazil and Mexico show comparatively higher average trust in the president (T-7) and the army (T-1), respectively. In contrast, Peru and Paraguay record relatively low levels of trust in congress and political parties.

These patterns align with structural indicators. Uruguay scores highest on the democracy index and the corruption perception index (indicating lower perceived corruption), while Venezuela and Nicaragua perform considerably worse on both. Similarly, economic and social development varies widely: Chile and Uruguay report the highest average GDP per capita, while Nicaragua and Honduras are at the lower end of the regional distribution. Urbanization rates also differ markedly, from very high levels in Uruguay to much lower ones in Guyana, reflecting contrasting population distributions and development paths

Regarding environmental indicators, Paraguay and Uruguay indicate the highest levels of general and specific tree cover loss, while Guyana records the lowest. This variation suggests uneven exposure to environmental pressures and differences in forest governance across the region.

3.6.1 Exploratory Factor Analysis (EFA)

To create an aggregated construct for trust in public institutions, an exploratory factor analysis (EFA) with *varimax rotation* is conducted on seven trust variables. As presented in the Appendix (Table C.3, Figure C.1), the scree plot analysis suggests the presence of a single latent dimension for institutional trust. All variables load positively on the first factor, with loadings ranging from 0.6179 (trust in the army) to 0.7752 (trust in congress). This result indicates that each item contributes meaningfully to the aggregated indicator, though to varying degree. Trust in congress, elections, and political parties show particularly strong associations with the factor, implying a central role for political institutions within this latent dimension.

Additionally, to assess the internal consistency of the institutional trust indicators, *Cronbach's alpha* is calculated. The resulting reliability coefficient is $\alpha = 0.83$, indicating a high level of internal consistency. This indicates that the selected trust variables are sufficiently correlated, justifying their aggregation into a single index of institutional trust.

3.7 Methodology

To test the research hypotheses, this study adopts a macro-panel analytical framework that combines cross-country and time-series data. The unit of analysis is the individual survey response, nested within country-year strata, which enables the assessment of how environmental change interacts with broader sociopolitical and economic dynamics. All variables are standardized to ensure comparability of effect sizes and to facilitate interpretation across models.

To properly account for the complex sampling design of the *AmericasBarometer* survey, the provided sampling weights (`wt`, `weight1500`) and stratification variables (`estratopri`, `strata`) were harmonized and applied across survey waves. Where necessary, a combined stratification variable was constructed to identify country-year sampling strata, preserving the integrity of the original design while enabling pooled analysis across space and time. Following *AmericasBarometer*'s technical guidelines, models were estimated using survey-weighted linear regression (`svy: regress`) with Taylor-linearized standard errors clustered at the primary sampling unit (PSU) level. This approach adjusts for unequal probabilities of selection, stratification, and intra-cluster correlation.

3.7.1 Fixed effects models

Given the potential for unobserved heterogeneity across countries and temporal dynamics affecting institutional trust, the main estimation strategy relies on linear fixed effects (FE) models with country and year fixed effects (Wooldridge, 2012). This approach controls for all time-invariant characteristics at the country level – such as geography, culture, or long-term institutional legacies – as well as time-varying global shocks that may uniformly affect all countries in a given year (e.g., global recessions, pandemics, international political trends).

By absorbing this structure, the model estimates are based on within-country variation over time, rather than on potentially confounded between-country differences. The coefficients reflect how changes within a country (i.e., rising tree cover loss) relate to changes in institutional trust, net of persistent national characteristics. In contrast, between-country variation is absorbed by fixed effects and does not directly influence the estimates. This makes the FE approach particularly suitable for studying dynamic processes such as environmental degradation and its implications for perceived institutional legitimacy.

To strengthen causal inference, all independent variables – including general and specific tree cover loss – are lagged by one year relative to the dependent variable, institutional trust. For example, tree cover loss and GDP per capita measured in 2022 are matched with institutional trust reported in 2023. This temporal alignment reduces concerns about reverse causality and enhances the plausibility of a causal interpretation.

The baseline model is specified as follows:

$$\text{Trust}_{it} = \beta_1 \text{TreeLoss}_{it-1} + \beta_2 X_{it-1} + \alpha_i + \gamma_t + \varepsilon_{it}$$

where Trust_{it} denotes the institutional trust outcome for individual i at time t in country c; TreeLoss_{it-1} is the forest cover loss measure lagged by one year (either general or specific); X_{it-1} includes lagged time-varying covariates such as standardized GDP per capita, quality of democracy, perceived corruption, and urbanization rate. α_i are the country fixed effects, γ_t year fixed effects, and ε_{it} is the idiosyncratic error term. The reference categories are Argentina for countries and 2008 for years.

The panel structure is unbalanced, as some country-year combinations are missing due to non-response or incomplete coverage in specific *AmericasBarometer* waves. This does not compromise the validity of the FE estimation, provided that missingness is not systematically correlated with the unobserved time-varying determinants of institutional trust. As Wooldridge (2012) notes, FE models apply equally well to unbalanced panels, using the available observations for each unit. To ensure sufficient within-unit variation, only countries with at least four valid survey waves are retained, and degrees of freedom adjusted accordingly.

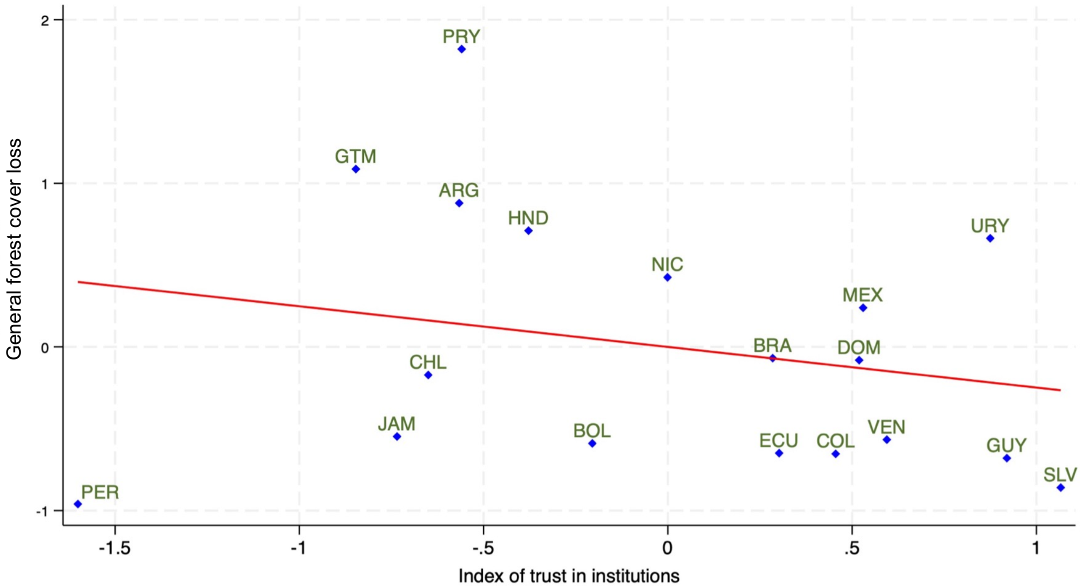
3.8 Results

3.8.1 Institutional trust index

The first analysis used institutional trust index as the dependent variable. To ensure model stability and interpretability, variance inflation factor (VIF) diagnostics were conducted for both models; results are presented in the Appendix (Table C.4). The independent variables of interest related to forest cover loss showed no signs of problematic multicollinearity. The democracy index, while moderately correlated with other structural variables (VIF = 27.76 in both models), retains theoretical relevance and independent explanatory power. Moreover, its correlation with the key independent variables is minimal (0.0148 with general tree cover loss and 0.0053 with specific tree cover loss). Since the democracy index is not a primary variable of interest, its multicollinearity does not pose a serious concern and was retained in the model.

According to Figure 3.1, the relationship between tree cover loss and institutional trust is clearly negative. The figure plots the conditional association between the two variables, based on residuals from separate regressions of tree cover loss and institutional trust on the same set of controls. The downward slope indicates that countries with higher levels of tree cover loss tend to exhibit lower levels of institutional trust. This supports the hypothesis that forest cover loss may be interpreted by citizens as sign of governance failure in addressing environmental degradation, thereby weaking confidence in public institutions.

Figure 3.1: Relationship between general forest cover loss and institutional trust in LAC, 2008–2023



*Note: Residuals were obtained from two separate OLS regressions: (i) institutional trust on GDP per capita, democracy index, perceived corruption index, and urbanization rate; and (ii) general tree cover loss on the same set of covariates. Country labels are abbreviated using the ISO 3166-1 alpha-3 standard. Each country is represented by a 3-letter code (*ARG = *Argentina,* BOL = *Bolivia,* BRA = *Brazil,* CHL = *Chile,* COL = *Colombia,* DOM = *Dominican Republic,* ECU = *Ecuador,* SLV = *El Salvador,* GTM = *Guatemala,* GUY = *Guyana,* HND = *Honduras,* JAM = *Jamaica,* MEX = *Mexico,* NIC = *Nicaragua,* PRY = *Paraguay,* PER = *Peru,* URY = *Uruguay,* VEN = *Venezuela). Full regression results are available in the Appendix (Table C.5).*

3.8.1.1 General forest cover loss

The results for the model using general tree cover loss (Table 3.1) indicate a statistically significant negative association with institutional trust (β = –0.0275, p < 0.001). In practical terms, when general tree cover loss increases – in areas with an initial canopy cover of ≥10% – trust in public institutions tends to decline. A one-standard deviation increase in general tree cover loss corresponds to a 0.027 standard deviation decrease in institutional trust. This effect remains robust after including controls, suggesting that environmental degradation consistently undermines citizens' confidence in institutions.

Among the control variables, GDP per capita shows a small but significant negative association with institutional trust (β = –0.0179, p = 0.004), implying that, net of other factors, countries with higher income levels report slightly lower levels of trust. Similarly, urbanization is negatively related to trust (β = –0.0352, p < 0.001), indicating that more urbanized contexts may foster greater institutional skepticism. An unexpected result emerges for the democracy index: a one-standard deviation increase in perceived democratic quality corresponds to 0.072 standard deviation decline in trust (β = –0.0716, p < 0.001). While counterintuitive, this may suggest that in some political contexts democratic institutions are perceived as ineffective, unresponsive, or complicit in broader governance failures. By contrast, lower perceived corruption is strongly and positively associated with institutional trust (β = 0.1841, p < 0.001), confirming the central role of institutional integrity in sustaining public confidence.

Country-level fixed effects also reveal some differences. Compared to Argentina – the reference category – El Salvador (β = 0.2845, p < 0.001), Uruguay (β = 0.2383, p < 0.001), Mexico (β = 0.2300, p < 0.001), Guyana (β = 0.1921, p < 0.000), and Nicaragua (β = 0.1789, p < 0.001) report significantly higher levels of institutional trust. In contrast, Peru exhibits a significant deficit (β = –0.2584, $p < 0.001$), indicating comparatively lower overall trust than the regional average.

Regarding temporal dynamics, institutional trust increased modestly in the years immediately following 2008 (2009-2012). However, from 2013 onwards, a marked and persistent decline is observed, particularly in 2018 and 2023. This pattern may reflect a broader regional erosion of institutional trust linked to political, social, and governance crises.

Finally, although the model explains only a modest share of variance in institutional trust ($R^2 \approx 0.0064$), this is expected given the multidimensional nature of the concept. Trust is shaped by a wide range of unobservable cultural, historical, ideological, and psychological factors, many of which are difficult to capture quantitatively in a region as politically and culturally diverse as LAC.

3.8.1.2 Specific forest cover loss

The second model considered specific tree cover loss as the independent variable, corroborating the findings of the general model (Table 3.2). This measure captures tree cover loss in areas with denser canopy thresholds (≥50% and ≥70%). The effect remains negative and significant (β = –0.0225, $p = 0.003$), although somewhat smaller than in the general model. One possible explanation for this difference is that that general tree cover loss may be more visible or widely perceived by the public, whereas specific tree cover loss may occur in more remote or less populated regions, with a less immediate impact on institutional trust. A graphical representation of the relationship is provided in the Appendix (Figure C.2).

All other covariates perform similarly to those in the general tree cover loss model, confirming the robustness of the relationship across specifications. Moreover, country-level and year-level effects show very patterns highly coherent with those observed in the general model.

Nevertheless, the significant association between forest cover loss and declining institutional trust emerges clearly across both models. This suggests that environmental degradation – expressed here as forest cover loss – is perceived by citizens as a sign of institutional weakness or failure in fulfilling public responsibilities. The stability of the tree cover loss coefficient across model specifications further strengthens confidence in the robustness and reliability of the findings.

Table 3.1: Impact of general tree cover loss on institutional trust in LAC, 2008–2023

	β	*SE*	*p*	*95% CI*	
General tree cover loss	–0.0275	0.0077	0.000	–0.0426	–0.0124
GDP per capita	–0.0179	0.0063	0.004	–0.0303	–0.0056
Democracy index	–0.0716	0.0110	0.000	–0.0933	–0.0499
Corruption perception index	0.1841	0.0208	0.000	0.1434	0.2249
Urbanization rate	–0.0352	0.0053	0.000	–0.0456	–0.0248
Countries					
Bolivia	–0.0619	0.0392	0.114	–0.1387	0.0149
Brazil	0.0702	0.0277	0.011	0.0159	0.1245
Chile	–0.0111	0.0539	0.837	–0.1168	0.0946
Colombia	0.0854	0.0272	0.002	0.0320	0.1388
Dominican Republic	0.1599	0.0266	0.000	0.1078	0.2119
Ecuador	0.1226	0.0295	0.000	0.0648	0.1804
El Salvador	0.2845	0.0357	0.000	0.2146	0.3545

Guatemala	–0.0120	0.0323	0.709	–0.0753	0.0512
Guyana	0.1921	0.0443	0.000	0.1052	0.2790
Honduras	0.0575	0.0358	0.108	–0.0126	0.1276
Jamaica	–0.0795	0.0271	0.003	–0.1326	–0.0263
Mexico	0.2300	0.0274	0.000	0.1762	0.2838
Nicaragua	0.1789	0.0403	0.000	0.0999	0.2579
Paraguay	0.0194	0.0325	0.550	–0.0442	0.0831
Peru	–0.2584	0.0254	0.000	–0.3082	–0.2087
Uruguay	0.2383	0.0585	0.000	0.1236	0.3531
Venezuela	0.1469	0.0433	0.001	0.0620	0.2318
Years					
2009	0.2482	0.0499	0.000	0.1504	0.3460
2010	0.1381	0.0161	0.000	0.1066	0.1696
2011	0.1799	0.0450	0.000	0.0918	0.2680
2012	0.0867	0.0228	0.000	0.0420	0.1315
2013	–0.2708	0.0480	0.000	–0.3649	–0.1766
2014	–0.0673	0.0175	0.000	–0.1016	–0.0330
2017	–0.0624	0.0167	0.000	–0.0952	–0.0297
2018	–0.2741	0.0461	0.000	–0.3646	–0.1836
2019	–0.1332	0.0168	0.000	–0.1661	–0.1003
2023	–0.2278	0.0169	0.000	–0.2610	–0.1945
Constant	–0.0459	0.0236	0.052	–0.0922	0.0005
F statistic			113.70***		
R^2			0.0064		
N. Obs.			184,989		

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively*

Table 3.2: Impact of specific tree cover loss on institutional trust in LAC, 2008–2023

	β	*SE*	*p*	*95% CI*	
Specific tree cover loss	–0.0225	0.0076	0.003	–0.0373	–0.0077
GDP per capita	–0.0166	0.0065	0.011	–0.0294	–0.0037
Democracy index	–0.0721	0.0111	0.000	–0.0938	–0.0504
Corruption perception index	0.1846	0.0208	0.000	0.1438	0.2254
Urbanization rate	–0.0348	0.0053	0.000	–0.0452	–0.0244
Countries					
Bolivia	–0.0585	0.0391	0.134	–0.1352	0.0181
Brazil	0.0696	0.0278	0.012	0.0151	0.1240
Chile	–0.0095	0.0540	0.860	–0.1154	0.0962
Colombia	0.0928	0.0271	0.001	0.0397	0.1460
Dominican Republic	0.1643	0.0266	0.000	0.1121	0.2165
Ecuador	0.1302	0.0293	0.000	0.0727	0.1876
El Salvador	0.2950	0.0355	0.000	0.2255	0.3646
Guatemala	–0.0125	0.0327	0.702	–0.0765	0.0516
Guyana	0.2033	0.0441	0.000	0.1169	0.2897
Honduras	0.0621	0.0362	0.086	–0.0089	0.1331

Jamaica	–0.0708	0.0268	0.008	–0.1233	–0.0183
Mexico	0.2399	0.0271	0.000	0.1868	0.2930
Nicaragua	0.1826	0.0408	0.000	0.1027	0.2626
Paraguay	0.0070	0.0319	0.825	–0.0554	0.0695
Peru	–0.2511	0.0252	0.000	–0.3004	–0.2017
Uruguay	0.2364	0.0589	0.000	0.1209	0.3519
Venezuela	0.1519	0.0435	0.000	0.0666	0.2372
Years					
2009	0.2412	0.0498	0.000	0.1434	0.3389
2010	0.1383	0.0161	0.000	0.1068	0.1699
2011	0.1774	0.0450	0.000	0.0892	0.2656
2012	0.0864	0.0229	0.000	0.0415	0.1313
2013	–0.2729	0.0481	0.000	–0.3673	–0.1786
2014	–0.0680	0.0178	0.000	–0.1029	–0.0332
2017	–0.0684	0.0164	0.000	–0.1006	–0.0362
2018	–0.2767	0.0461	0.000	–0.3671	–0.1863
2019	–0.1364	0.0171	0.000	–0.1699	–0.1030
2023	–0.2294	0.0173	0.000	–0.2633	–0.1955
Constant	–0.0483	0.0237	0.042	–0.0948	–0.0018
F statistic			113.82***		
R^2			0.0064		
N. Obs.			184,989		

*Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008. The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

3.8.2 Institutional trust items

In Table 3.3 and Table 3.4, the disaggregated analysis of institutional trust items confirms the pattern observed in the aggregated index models. The negative relationship with forest cover loss is strongest and most robust for trust in the army ($\beta = –0.0306$, $p < 0.001$ in the general model), elections ($\beta = –0.0283$, $p < 0.001$), congress ($\beta = –0.0260$, $p < 0.001$), and political parties ($\beta = –0.0230$, $p < 0.001$). In each of these domains, higher levels of tree cover loss correspond to lower public confidence.

By contrast, the effect is weaker or absent for institutions operating at more local or operational levels, such as municipality, the police, or the president. For municipality, the relationship is slightly positive but modest ($\beta = 0.0108$, $p = 0.082$), while for the police and the president no statistically significant effects are observed.

These findings suggest that citizens do not primarily associate forest cover loss with local administrations or law enforcement bodies but rather perceive it as evidence of broader governance failure. Specifically, forest cover loss appears to undermine trust in institutions tied to democratic representation and legitimacy, such as congress, political parties, and elections. Even if the effect is not always direct, this pattern indicates that forest cover loss is widely perceived as a sign of political failure, state neglect, and the inability of institutions to safeguard collective interests.

More details regarding estimates for institutional trust items are presented in the Appendix (Table C.6 and others).

Table 3.3: Impact of general tree cover loss on institutional trust items in LAC, 2008–2023

	T–1	T–2	T–3	T–4	T–5	T–6	T–7
General tree cover loss	–0.0306***	–0.0283***	–0.0260***	0.0108*	–0.0230***	0.0001	–0.0070
	(0.0053)	(0.0057)	(0.0047)	(0.0062)	(0.0051)	(0.0062)	(0.0069)
GDP per capita	–0.0075	–0.0015	–0.0085**	–0.0338***	–0.0054	0.0018	–0.0142**
	(0.0049)	(0.0047)	(0.0040)	(0.0054)	(0.0047)	(0.0053)	(0.0061)
Democracy index	0.0264***	–0.0465***	–0.0690***	–0.0437***	–0.0638***	0.0188**	–0.0914***
	(0.0079)	(0.0077)	(0.0066)	(0.0083)	(0.0076)	(0.0084)	(0.0100)
Corruption perception index	0.0921***	0.0939***	0.1574***	0.0602***	0.1907***	0.1302***	–0.0213
	(0.0155)	(0.0151)	(0.0142)	(0.0165)	(0.0148)	(0. 0164)	(0.0200)
Urbanization rate	–0.0315***	–0.0240***	–0. 0218***	–0.0130***	–0.0145***	–0. 0083***	–0.0316***
	(0.0038)	(0.0038)	(0.0033)	(0.0042)	(0.0036)	(0.0041)	(0.0049)
Constant	–0.3021***	0.1180	0.0418	0.0280***	–0.0563***	0.1369***	–0.0975***
	(0.0195)	(0.0170)	(0.0132)	(0.0195)	(0.0148)	(0.0199)	(0.0209)
F statistic	72.68***	199.04***	139.12***	68.10***	93.95***	147.65***	138.40***
R^2	0.0116	0.0086	0.0121	0.0047	0.0052	0.0120	0.0064
N. Obs.	197,406	197,925	194,479	198,596	198,108	200,532	200,532

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008. T-1, Trust in army; T-2, Trust in elections; T-3, Trust in congress; T-4, Trust in municipality; T-5, Trust in political parties; T-6, Trust in police; T-7, Trust in president.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table 3.4: Impact of specific tree cover loss on institutional trust items in LAC, 2008–2023

	T–1	T–2	T–3	T–4	T–5	T–6	T–7
Specific tree cover loss	–0. 0279***	–0. 0240***	–0.0205***	0. 0121*	–0. 0217***	–0. 0002	–0. 0022
	(0.0052)	(0.0056)	(0.0046)	(0.0062)	(0.0050)	(0.0061)	(0.0068)
GDP per capita	–0. 0052	0.0001	–0.0074*	–0. 0352***	–0. 0035	0. 0018	–0. 0147**
	(0.0050)	(0.0049)	(0.0041)	(0.0056)	(0. 0049)	(0.0055)	(0.0063)
Democracy index	0. 0255***	–0. 0471***	–0. 0694***	–0. 0432***	–0. 0645***	0. 0188**	–0. 0914***
	(0.0079)	(0.0077)	(0. 0066)	(0.0083)	(0. 0076)	(0.0084)	(0.0100)
Corruption perception index	0. 0925***	0. 0943***	0. 1580***	0. 0603***	0. 1909***	0. 1302***	–0. 0210
	(0.0146)	(0.0151)	(0. 0143)	(0. 0165)	(0. 0149)	(0.0164)	(0.0200)
Urbanization rate	–0. 0314***	–0. 0237***	–0. 0213***	–0. 0127***	–0. 0145***	–0. 0084**	–0.0310***
	(0.0038)	(0.0038)	(0.0033)	(0.0042)	(0.0036)	(0.0041)	(0.0049)
Constant	–0. 3035***	0. 1159***	0.0392***	0. 0276***	–0. 0555***	–0.1367***	–0. 0996***
	(0.0197)	(0. 0170)	(0. 0133)	(0.0194)	(0. 0147)	(0. 0199)	(0. 0209)
F statistic	72.50***	198.84***	138.37***	68.13***	94.05***	147.48***	138.33***
R^2	0.0116	0.0086	0.0121	0.0047	0.0052	0.0120	0.0064
N. Obs.	197,406	197,925	194,479	198,596	198,108	200,532	200,532

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008. T-1, Trust in army; T-2, Trust in elections; T-3, Trust in congress; T-4, Trust in municipality; T-5, Trust in political parties; T-6, Trust in police; T-7, Trust in president.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

3.9 Robustness checks

3.9.1 Between-within decomposition: approach

To deepen the analysis of how tree cover loss affects institutional trust, a *between-within decomposition* approach is applied to the pooled panel dataset. This method separates the structural variation between countries from temporal variation within countries, allowing for a more nuanced interpretation of how environmental change relates to institutional confidence.

Following Raudenbush & Bryk (2002), a time-varying predictor X_{it} is decomposed into two components: the country mean $\bar{X}_i$, capturing *between-country* effects, and the deviation from that mean $(X_{it} - \bar{X}_i)$, capturing *within-country* effects. This "manifest aggregation" approach (Marsh *et al.*, 2009; Lüdtke *et al.*, 2011) treats observed country means as proxies for group-level characteristics. While not free from measurement error (Guo *et al.*, 2021), it remains a widely used strategy to disentangle contextual (*between*) and dynamic (*within*) influences.

This decomposition is relevant for institutional trust, which may respond to short-term environmental shocks (i.e., annual shifts in tree cover loss) and long-term structural conditions (i.e., historical tree cover loss). To reduce risks of simultaneity and ensure temporal ordering, tree cover loss and other time-varying covariates are lagged by one year relative to institutional trust, consistent with the fixed effects models.

The model is specified as follows:

$$\text{Trust}_{it} = \beta_W(\text{TreeLoss}_{it-1} - \overline{\text{TreeLoss}_i}) + \beta_B\overline{\text{TreeLoss}_i} + \beta_2 X_{it-1} + \alpha_i + \gamma_t + \varepsilon_{it}$$

where β_W estimates the effect of temporal (within-country) variation in lagged tree cover loss, while β_B estimates the structural (*between-country*) association based on long-term country means. X_{it-1} includes lagged controls (GDP per capita, quality of democracy, perceived corruption, and urbanization rate). α_i and γ_t denote country and year fixed effects.

This specification makes it possible to assess whether institutional trust is more sensitive to short-term environmental deterioration or to enduring ecological conditions across countries, while maintaining consistency with the main lagged fixed-effects design.

3.9.2 Between-within decomposition: results

The between-within regression confirms the negative association between tree cover loss and institutional trust identified in the previous analyses. Both short-term environmental changes (within-country variation) and long-term structural degradation (between-country differences) are significantly related with lower levels of trust in public institutions.

As presented in Table 3.5, a one-standard-deviation increase in annual tree cover loss *within* a country is associated with a 0.017 standard-deviation decrease in institutional trust ($\beta = -0.017$, $p < 0.001$), indicating that recent environmental deterioration erodes public confidence in institutions. By contrast, a one-standard-deviation increase in average tree cover loss across countries corresponds to a 0.111 standard deviation decrease in institutional trust ($\beta = -0.111$, $p < 0.001$), suggesting that persistent forest cover loss is strongly linked to diminished confidence in institutions. The same analysis performed with specific tree cover loss yields similar patterns, with detailed results presented in the Appendix (Table C.20).

Figure 3.2 and Figure 3.3 visualize the effects of between- and within-country decomposition. While the within-country association is negative, the effect smaller and statistically weaker compared to the between-country variation. This does not imply the absence of an effect but rather reflects the multifactorial nature of institutional trust, where environmental degradation is one of several concurrent determinants. Structural cross-country differences therefore appear to provide a clearer identification of long-term patterns, whereas within-country dynamics are more likely shaped by multiple contextual factors.

In conclusion, these findings remain robust after adjusting for controls, supporting the hypothesis that acute and chronic forest cover loss undermine public perceptions of institutional effectiveness and environmental stewardship.

Table 3.5: Between-within regression of institutional trust on general tree cover loss

DV: Institutional trust	*β*	*SE*	*p*	*95% CI*	
Within-country (deviation)					
Yearly tree cover loss	–0.0167	0.0047	0.000***	–0.0258	–0.0075
Between-country (mean)					
Average tree cover loss	–0.1110	0.0256	0.000***	–0.1609	–0.0607
GDP per capita	–0.0179	0.0063	0.004***	–0.0303	–0.0056
Democracy index	–0.0716	0.0110	0.000***	–0.0933	–0.0499
Corruption perception index	0.1841	0.0208	0.000***	0.1434	0.2249
Urbanization rate	–0.0352	0.0053	0.000***	–0.0456	–0.0248
Countries					
Bolivia	–0.1446	0.0360	0.000***	–0.2151	–0.0741
Brazil	0.0066	0.0290	0.820	–0.0502	0.0634
Chile	–0.0878	0.0639	0.170	–0.2132	0.0375
Colombia	–0.0307	0.0373	0.410	–0.1038	0.0424
Dominican Republic	0.1061	0.0222	0.000***	0.0626	0.1497
Ecuador	–0.0105	0.0311	0.735	–0.0715	0.0504
El Salvador	0.1677	0.0405	0.000***	0.0882	0.2471
Guatemala	0.0673	0.0485	0.165	–0.0277	0.1623
Guyana	–0.0015	0.0551	0.979	–0.1095	0.1066
Honduras	0.0881	0.0410	0.032**	0.0077	0.1685
Jamaica	–0.2161	0.0421	0.000***	–0.2986	–0.1336
Mexico	0.1279	0.0282	0.000***	0.0725	0.1833
Nicaragua	0.2048	0.0448	0.000***	0.1169	0.2927
Paraguay	0.1525	0.0613	0.013**	0.0323	0.2727
Peru	–0.3969	0.0363	0.000***	–0.4680	–0.3258
Uruguay	0.3468	0.0559	0.000***	0.2372	0.4564
Years					
2009	0.2482	0.0499	0.000***	0.1504	0.3460
2010	0.1381	0.0161	0.000***	0.1066	0.1696
2011	0.1799	0.0450	0.000***	0.0918	0.2680
2012	0.0867	0.0228	0.000***	0.0420	0.1315
2013	–0.2708	0.0480	0.000***	–0.3649	–0.1766
2014	–0.0673	0.0175	0.000***	–0.1016	–0.0330
2017	–0.0624	0.0167	0.000***	–0.0952	–0.0297
2018	–0.2741	0.0461	0.000***	–0.3646	–0.1836
2019	–0.1332	0.0168	0.000***	–0.1661	–0.1003
2023	–0.2278	0.0169	0.000***	–0.2610	–0.1945
Constant	0.0085	0.0219	0.698	–0.0344	0.0513
F statistic			113.70***		
R^2			0.0064		
N. Obs.			184,989		

*Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008. The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively*

Figure 3.2: Effect of between-country tree cover loss on trust in institutions

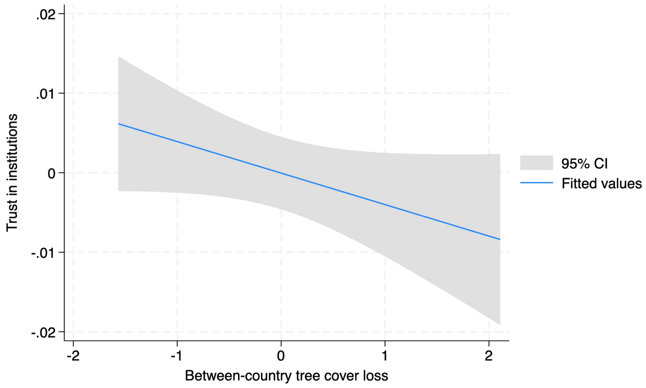
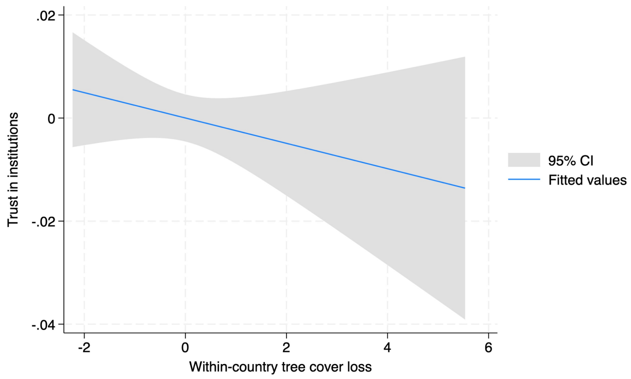


Figure 3.3: Effect of within-country tree cover loss on trust in institutions



3.10 Discussion

The findings for general and specific forest cover loss extend existing evidence on the political consequences of environmental degradation, showing that forest cover loss is associated with a measurable decline in public trust in institutions. Similar dynamics have been observed in disaster-prone contexts, such as wildfires or earthquakes, where environmental hazards often erode public confidence in government agencies.

These results align with the *associationist* model of trust (Eiser *et al.*, 2002; Bronfman *et al.*, 2008), which views trust as a consequence of public attitudes toward environmental issues. In this sense, persistent exposure to tree cover loss may reinforce distrust in institutions, particularly when governments are perceived as failing to respond effectively. This interpretation is coherent with the between-within decomposition analysis: while short-term (*within-country*) effects are weaker, long-term structural forest loss (*between-country*) reports a stronger negative association with institutional trust, suggesting that enduring ecological decline undermines legitimacy more deeply than temporary fluctuations, which might be shaped by country-specific factors such as institutional capacity, historical governance, or media environments.

Although the existing literature has not directly examined the link between forest loss and declines in institutional trust, comparative evidence from related areas reinforces this interpretation. In Chile, low institutional trust correlates with perceived risk of environmental hazards and weak disaster preparedness (Bronfman *et al.*, 2016). In Greece, wildfires exacerbated existing mistrust across a wide range of institutions, especially where social cohesion was already fragile. Institutional mistrust – especially toward the military and media – was significantly related to heightened hostility. Among disaster victims, this loss of confidence translated into an erosion of civic values such as dialogue, mutual support, and rule compliance (Adamis & Papanikolaou, 2011; Papanikolaou *et al.*, 2012). Evidence from Southern California further illustrates the ambivalent dynamics of trust erosion and partial restoration in wildfire emergency management. On one hand, poor institutional communication fueled distrust, indicating a disconnect between institutions and the public. On the other, respondents expressed willingness to support wildfire-related taxation for preventive measures, suggesting that a residual level of trust in institutional capacity persists when resources are adequately allocated (Masri *et al.*, 2023). These examples support the idea that environmental degradation does not automatically erode trust. Instead, its political consequences depend on institutional responsiveness and accountability. Perceived inaction or incapacity may weaken legitimacy, while effective responses can mitigate or even restore public confidence.

The role of covariates also provides valuable insights. The negative association between GDP per capita and institutional trust, although counterintuitive, resonates with findings from other regions, where high economic development without redistribution may foster perceptions of injustice, inefficiency, or elite capture (Medve-Bálint & Boda, 2014; Moramarco & Palmisano, 2023; Revtiuk, 2024). These interpretations allude to the fact that increasing average income alone is not sufficient to foster trust in public institutions. What appears to matter more are the modalities of income distribution, citizens' perceptions of fairness, and the extent to which institutional performance is seen as legitimate and inclusive. In LAC, this may reflect structural tensions between growth and inequality, where rising incomes do not necessarily translate into greater institutional legitimacy.

The urbanization effect confirms that rapid or poorly managed expansion can strain social cohesion and weaken public confidence. Henderson & Wang (2007) and Angino *et al.* (2022) emphasized that when local institutions fail to keep pace with urban expansion, perceived inefficiencies or weak accountability can further diminish public trust. In LAC, urban growth is often associated with informal settlements, infrastructural deficits, and social fragmentation, echoing studies from China and Africa which showed that urbanization reduces community trust when neighborhood heterogeneity increases and services or opportunities are unequally distributed (Xu *et al.*, 2023; Sakketa, 2023).

By contrast, the positive association between lower perceived corruption and trust is well documented in the literature. Corruption perceptions at national and local levels can deeply erode institutional legitimacy, reducing citizens' willingness to comply with rules or engage in civic life. Conversely, transparency and accountability act as functional pillars of institutional legitimacy and effective governance, in particular in regions where political scandals, clientelism, and weak enforcement mechanisms have historically undermined trust in the state (Boly & Gillanders, 2022; Beesley & Hawkins, 2022).

Lastly, the negative coefficient for democracy index aligns with arguments that personalized electoral systems in Latin America expose institutions to greater volatility in public confidence (Ross & Escobar-Lemmon, 2011). These systems raise expectations and strengthen perceived political responsiveness, but they also magnify disillusion when democratic institutions are seen as failing to deliver stability and effective governance.

Taken together, these findings support the hypotheses that institutional trust in LAC is shaped not only by structural governance factors but also by how environmental degradation interacts with inequality, urbanization, corruption, and democratic responsiveness. This illustrates a broader associationist model of trust, in which risk perception and institutional trust are not directly causally linked, but rather jointly shaped by underlying public attitudes and local experiences. Ultimately, forest cover loss, as a visible yet politically underestimated environmental challenge, appears as a litmus test for institutional legitimacy and stability in the region.

3.11 Conclusion

This study provides new empirical evidence that forest cover loss is significantly associated with a measurable decline in trust in public institutions across LAC from 2008 to 2023. By integrating general and specific measures of tree cover loss into fixed-effects panel models, the study extends existing literature on the political consequences of environmental degradation, showing that persistent exposure to ecological damage can progressively erode institutional confidence. The erosion of trust is most pronounced for institutions linked to national governance, such as congress, political parties, and elections, while local institutions are less affected. This pattern can be explained by citizens' perception of national authorities as more directly involved and responsible for addressing large-scale environmental challenges.

The results align with the *associationist model* of trust, which views institutional trust as a consequence of public attitudes toward environmental issues. In this perspective, distrust emerges not solely from objective evaluations of institutional performance, but also from forms of trust as a construct shaped by collective memory and historical patterns of institutional responses. Moreover, what matters is not institutional performance alone, but whether the public perceives it as fair, inclusive, and serving the collective good – perceptions that can determine whether trust is sustained, eroded, or rebuilt. This interpretation is reinforced by the between-within decomposition analysis. It consistently presents a negative relationship between environmental degradation and citizens' confidence in public institutions. The effect is stronger in the long term – where persistent forest cover loss predicts institutional disaffection – than in the short term, where annual within-country changes yield weaker effects, likely mediated by country-specific factors.

Additionally, the findings hold across models controlling for key structural and sociopolitical variables. The findings highlight the importance of broader contextual drivers, such as persistent economic inequality, rapid and uneven urbanization, and perceived corruption, all emerging as crucial determinants of institutional legitimacy.

In summary, these results align with a growing body of literature recognizing environmental governance as a factor shaping public perceptions of state legitimacy. When forest cover loss is widespread or poorly managed, especially in regions historically marked by inequality, infrastructural gaps, and limited civic accountability, it may amplify perceptions of state neglect or incapacity. In such contexts, forest cover loss is not merely an ecological issue; it becomes a social and political signal, reinforcing concerns of institutional fragility and uneven public service delivery. Finally, this analysis deepens the understanding of how environmental degradation carries significant sociopolitical costs, with important implications for sustainability and governance in Latin America and the Caribbean.

3.12 Policy implications

The evidence that forest cover loss is associated with measurable declines in institutional trust across LAC carries important implications for environmental governance and political stability in the region. Four main policy implications arise from this study.

First, strengthening institutional capacity and responsiveness to environmental degradation requires the implementation of transparent land-use regulations, effective sanctioning mechanisms, and targeted monitoring plans in vulnerable ecosystems. These interventions can send a strong signal of institutional commitment to environmental issues, while mitigating social pressures – including the erosion of public trust in institutions – and improving social and political stability.

Second, strengthening information channels and risk communication should be a priority for public engagement. National governments should invest in participatory decision-making, community-based forest management, and clear communication strategies that make environmental policies visible, accessible, and locally relevant. Such efforts can enhance citizens' perceptions of fairness, inclusivity, and responsiveness, thereby reinforcing trust in authorities and the institutional system.

Third, integrating environmental governance with broader sociopolitical reforms. The findings indicate that structural inequalities, urbanization pressures, and perceived corruption are powerful determinants of institutional legitimacy. Forest governance is more effective when embedded within broader strategies aimed at reducing inequality, managing urban growth, and strengthening transparency and accountability.

Fourth, tailored interventions should be prioritized over uniform and one-size-fits-all strategies. The between-within decomposition results indicate that country-specific historical and institutional contexts mediate the relationship between forest cover loss and institutional trust. National and local policies should therefore be grounded in a clear understanding of the country's specific environmental conditions, political history, governance traditions, and social priorities.

In conclusion, addressing forest cover loss is therefore not only an environmental mission but also a political priority in LAC. Restoring trust in countries with visible ecological damage will depend on institutions' ability to respond credibly, transparently, and inclusively to citizens' concerns. By coupling ecological management with inclusive governance practices, policymakers can mitigate the sociopolitical costs of environmental degradation and reinforce the social contract between citizens and the state.

3.13 Limitations

Despite the advantages of using harmonized public opinion data across LAC, several limitations of the AmericasBarometer survey design should be acknowledged.

First, the standardization of survey instruments across countries and years is not always perfect. Minor wording differences in question wording, as well as variations in the selection of survey years across countries, may affect the comparability of results.

Second, although post-stratification weights are applied, the risk of non-response bias remains, particularly in contexts of fragility and conflict where survey implementation may be compromised.

Third, the sampling frame might exclude populations living in remote rural areas. This can lead to the underrepresentation of groups such as Indigenous communities or residents in deforested areas, who may be disproportionately affected by environmental change.

Lastly, variations in survey timing across countries and years may introduce seasonal or political effects (e.g., surveys conducted during elections or crises) that year fixed effects cannot fully capture. Although robust sampling weights, clustering, and fixed effects help mitigate these risks, they cannot fully eliminate potential measurement error or threats of external validity.

These limitations indicate that findings should be interpreted with caution, especially regarding their generalization beyond surveyed populations. Nonetheless, the consistency of results across models and robustness checks increases confidence in the validity of the main conclusions.

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Conclusions

Final remarks and contributions to the literature

In this thesis, various non-material dimensions – such as social capital, subjective happiness, and the environment – influencing well-being and collective trust have been studied. Despite the different contexts and evaluation scales used, all three studies link the individual, community, and societal spheres as a unique entity sharing common vulnerabilities and potential strengths. The thesis maintains a human-centered perspective across all chapters, emphasizing social inclusion, public health, and democratic stability in Latin America and the U.S. The broad scope of this focus represents an attempt to stimulate social justice initiatives for individuals suffering mental health conditions and addictions, and to reinforce institutional confidence among those living in contexts where environmental fragility is an urgent and collective concern.

The first and second chapters identify underlying relationships that can inform public health initiatives for marginalized and underrepresented social groups, while the third chapter considers the indivisible relationship between individuals and the natural environment.

In particular, fieldwork data collection in Chapter 1 investigates mental health population in critical and poor areas of the urban peripheries of Fortaleza, Brazil. It examines the living conditions and well-being of individuals with psychiatric and psychological conditions, identifying potential interventions based on the therapeutic role of social capital, aimed at strengthening social participation and involvement and, consequently, enhancing their daily perceived quality of life.

Chapter 2 supports the social causation hypothesis of subjective happiness as a precursor of crack/cocaine use and injection drug use. Causal inference analysis detected a clear pathway whereby low levels of happiness increase the likelihood of substance use in the U.S. population. This perspective supports the crucial role of eudaimonic well-being – based on living a meaningful and satisfying life in harmony with personal life goals and relationships.

Chapter 3 emphasizes the relationship between human beings, the environment, and centers of institutional power. Latin America and the Caribbean is globally the most important area in terms of ecosystems, biodiversity, and forests. This study shows that forest loss in this region can be linked to a gradual erosion of social stability, solidarity, and institutional trust; in other words, it may reflect a declining society whose degradation of values follows the pace of human-driven environmental degradation.

Beyond the specific findings of each chapter, a unifying pattern emerges: well-being, trust, and social resilience cannot be adequately understood through purely economic or prohibitionist lenses. They are deeply shaped by social, psychological, and ecological determinants that connect individuals, communities, and institutions. The overall results therefore point to the need for more integrated social and public health strategies, where mental health care, substance use prevention, and environmental protection are not treated as separate challenges but as interdependent components of collective well-being and social stability.

In this sense, the thesis provides a multidisciplinary contribution to the literature. Chapter 1, through fieldwork data collection, offers a detailed view of hard-to-reach social and urban contexts, focusing on not only the living conditions of mental health populations but also the specific needs and characteristics of distinct mental health groups. Chapter 2 supports a clear directionality in the relationship between happiness and substance use, shedding light on the protective role of happiness in shaping patterns of crack/cocaine and injection drug use. Finally, Chapter 3 introduces a new perspective to the literature on democratic stability, institutional functioning, and social cohesion, by linking forest loss to trust in public institutions and encouraging institutional studies to integrate ecological determinants that are often overlooked.

This thesis also acknowledges some limitations. The first and the second chapters rely on cross-sectional data, which limits the possibility of tracing long-term causal pathways. The third chapter is based on an unbalanced cross-country panel, which may overlook idiosyncratic events. Since the analyses in Chapter 2 and Chapter 3 use secondary data sources, the range of available variables was constrained, and the distribution of some dependent variables required adjustments to ensure model stability. Nevertheless, the application of methods such as instrumental variables and nonparametric balancing techniques has strengthened the robustness of the results and increased their empirical reliability.

Future research should address these limitations by integrating longitudinal data, extending comparisons across different countries and regions, and combining quantitative analysis with qualitative perspectives to better capture the lived experiences behind statistical patterns. Particular attention should be given to vulnerable populations and fragile contexts, where inequalities in happiness, mental health, and institutional trust are most evident and where targeted interventions may have the strongest impact.

In conclusion, this thesis demonstrates that subjective happiness, social capital, and institutional trust are not marginal concerns but essential foundations of public health, social cohesion, and environmental sustainability. Recognizing and strengthening these dimensions is not only a scientific task but also a political and ethical responsibility for policymakers committed to building more inclusive, resilient, and human-centered societies.

Appendix A

Chapter 1 Appendix

Table A.1: Questionnaire description

1	**Gender:** man; woman; trans man; trans woman; non-binary; other, specify.
2	**Age:** 18-25; 26-35; 36-45; 46-55; 56-65; more than 65.
3	**Ethnicity**: black; light-brown skinned; white, indigenous, yellow (*amarelo*); other, specify.
4	**Marital status:** single; married; divorced or separated; widowed; engaged or living together.
5	**Neighborhood of residence:** indicate your neighborhood
6	**Employment status:** *What is your current job?* (Self-employed professional or business owner; public servant or military personnel; private sector employee; farmer; self-employed or service provider; paid domestic worker; intern; freelancer; homemaker; unemployed; retired; student; unpaid domestic work; other, specify)
7	**Financial well-being:** *Are you able to contribute to your family's financial needs with your income?* (I am not currently employed; I am still a student; no, my income alone is insufficient; yes, I can meet the financial needs, but with difficulty; yes, I can comfortably meet the financial needs)
8	**Education level:** *Have you attended school?* (I completed elementary school; I completed high school; I completed university; I have never attended school; I did not complete elementary school; I did not complete high school; I have a postgraduate degree; I am still attending school, specify grade/class)
9	**Indicate which technology items you have at home:** mobile phone; television; computer; internet connection.
10	**Social inclusion:** *Do you feel included and integrated into the community where you live?* (1 = No, and I am not interested; 2 = No, but I would like to be included; 3 = Yes, but I prefer to keep some distance; 3 = Yes, I feel included)
11	**Subjective happiness:** *Are you happy with your life?* (1 = not happy at all; 2 = not happy, but the situation is improving; 3 = happy, but I could be more; 4 = very happy)
12	**Self-reported general health:** *How would you describe your current well-being?* (1 = I am feeling unwell; 2 = I am not feeling well, but my condition is improving; 3 = I am feeling generally well, but there is room for improvement; I am feeling well)
13	**Mental health:** *In the last month, how many times have you had the following disorders?* (1 = never; 2 = few times; 3 = sometimes; 4 = often; 5 = every day) I have little interest or pleasure in doing things I have difficulty managing household tasks I have sleep disorders I have fatigue and loss of energy I have sad and depressive states, a feeling of devastation I have worry and anxiety I have nervousness, irritability, loss of control I have loss of attention, concentration I have stress, tension I use alcohol or drugs I have eating disorders (eating too much or too little) I have issues with self-harm
14	**Friendships:** *How many friends do you have?* (0 = I do not have friends; 1 = less than 5 friends; 2 = between 5 and 10 friends; 3 = more than 10 friends)
15	**Social meetings:** *How often do you meet with your friends or acquaintances?* (0 = I never or rarely meet with friends or acquaintances; 1 = At least once a year; 2 = At least once a month; 3 = More than once a week)
16	**Social participation:** *How often do you participate in events organized by your neighborhood associations (clubs, parties, courses, cultural, health, political, religious meetings, etc.)?* (0 = I never participate; 1 = Sometimes a year; 2 = Several times a month)
17	**Volunteering:** *Do you enjoy working with others to improve the life of your neighborhood?* (0 = no, I do not; 1 = yes, I do)
18	**Trust in institutions:** *How much trust do you have in the following institutions?* (1 = Very poor; 2 = Poor; 3 = Average; 4 = Good; 5 = Excellent) Trust in churches Trust in school Trust in police forces Trust in press Trust in national government Trust in local authorities

Table A.2: Kruskal-Wallis' and Dunn's test

Variables	Kruskal-Wallis test Chi-squared	Sig.	Dunn's test MSM – CAPS Z	p	SEM – MSM Z	p	SEM – CAPS Z	p
Gender (female)	10.252	0.006	2.271	0.046	–3.151	0.005	–1.111	0.266
Age	4.262	0.119						
Black, light–skinned black, indigenous	3.152	0.207						
Married	12.881	0.001	2.735	0.012	0.338	0.735	3.249	0.003
Occupational status (employed)	32.37	0.000	4.220	0.000	0.710	0.477	5.222	0.000
Retired	6.267	0.043	–1.531	0.252	–0.747	0.455	–2.437	0.044
Financial well–being	22.362	0.000	3.201	0.003	1.018	0.308	4.495	0.000
Education	19.200	0.000	3.158	0.003	0.681	0.496	4.074	0.000
Technological access	16.431	0.000	3.056	0.004	0.430	0.667	3.690	0.001
Self-reported general health	74.141	0.000	5.544	0.000	2.223	0.026	8.294	0.000
Mental health symptoms								
Tiredness	63.337	0.000	–5.160	0.000	–2.009	0.044	–7.654	0.000
Disability	52.484	0.000	–4.576	0.000	–1.981	0.000	–7.009	0.000
Insomnia	142.38	0.000	–6.251	0.000	–4.748	0.000	–11.841	0.000
Fatigue	86.079	0.000	–4.211	0.000	–4.363	0.000	–9.269	0.000
Depression	151.9	0.000	–5.185	0.000	–6.193	0.000	–12.324	0.000
Anxiety	114.58	0.000	–4.324	0.000	–5.548	0.000	–10.703	0.000
Nervousness	112.97	0.000	–4.028	0.000	–5.753	0.000	–10.621	0.000
Concentration	93.142	0.000	–5.469	0.000	–3.384	0.000	–9.504	0.000
Stress	82.337	0.000	–2.424	0.015	–5.778	0.000	–8.962	0.000
Social inclusion	36.447	0.000	4.536	0.000	0.666	0.506	5.506	0.000
Subjective happiness	88.044	0.000	4.527	0.000	4.142	0.000	9.356	0.000
Friendships	40.551	0.000	4.568	0.000	1.018	0.308	5.932	0.000
Social meetings	14.740	0.001	2.713	0.013	0.672	0.501	3.597	0.001
Social participation	4.950	0.084						
Volunteering	14.03	0.001	3.072	0.004	–0.004	0.997	3.224	0.004
Trust in institutions								
Trust in church	0.544	0.762						
Trust in school	8.505	0.014	–1.772	0.153	–0.884	0.377	–2.843	0.013
Trust in police forces	0.099	0.952						
Trust in press	1.337	0.513						
Trust in national government	1.699	0.427						
Trust in local authorities	0.283	0.868						

The Dunn's test was performed with the Holm method and p-values adjusted were reported.

Figure A.1: Parallel analysis scree plots

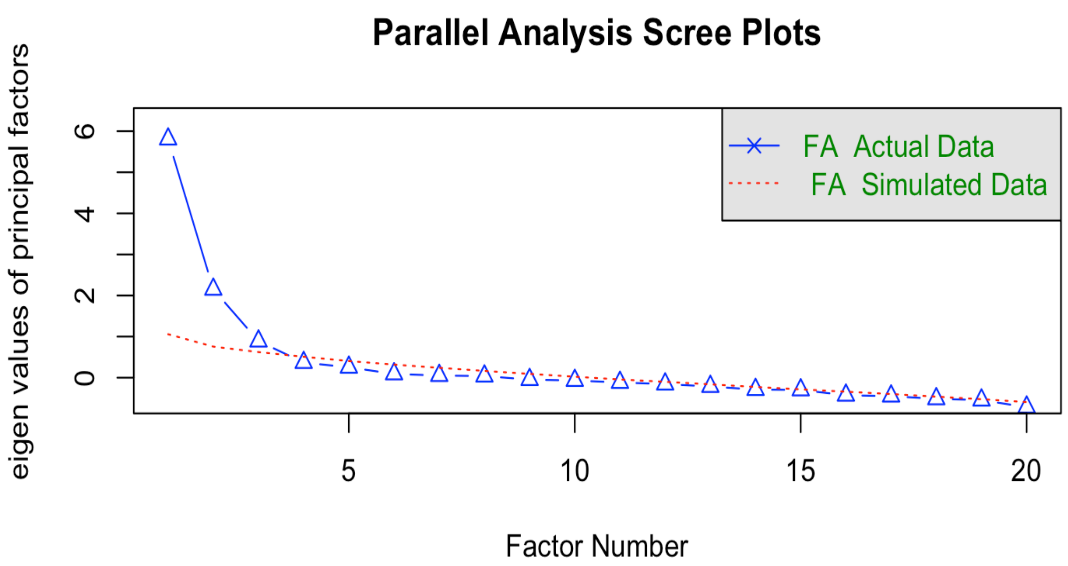


Table A.3: Exploratory Factor Analysis (EFA)

	ML1	ML2	ML3
Friendships			0.533
Social meetings			0.519
Social participation			0.490
Volunteering			0.573
Social inclusion			0.715
Tiredness	0.520		
Disability	0.620		
Fatigue	0.802		
Insomnia	0.721		
Depression	0.872		
Anxiety	0.823		
Nervousness	0.800		
Concentration	0.747		
Stress	0.738		
Trust in church		0.375	
Trust in school		0.506	
Trust in police		0.601	
Trust in press		0.607	
Trust in national government		0.725	
Trust in local authorities		0.824	
SS loadings	5.203	2.384	1.934
Proportion variance	0.260	0.119	0.097
Cumulative variance	0.260	0.379	0.476

According to the parallel analysis and scree plot, three factors were suggested based on the eigenvalue criterion (>1.00) (Kaiser, 1974). Following the guidelines of Field (2013), factor loadings above 0.30 were considered meaningful and are reported in the table. Items that failed to meet this threshold were removed. The first factor (ML1) represents mental health, the second factor (ML2) represents trust in institutions, and the third factor (ML3) represents social capital. The three factors explain 47.6% of the total variance.

Table A.4: Summary of balance for all data

	Pre matching			Post matching		
	Means T.	Means C.	SMD	Means T.	Means C.	SMD
Gender	0.7530	0.7610	-0.0185	0.7472	0.7528	-0.0130
Age	3.5299	3.0040	0.4251	3.2978	3.2472	0.0409
Ethnicity	0.8367	0.8008	0.0970	0.8427	0.8146	0.0760
Being married	0.4462	0.3187	0.2565	0.4494	0.3820	0.1356
Being retired	0.0996	0.1036	-0.0133	0.1067	0.1067	0.0000
Being employed	0.4980	0.3625	0.2709	0.4222	0.4000	0.0444
Financial well-being	2.4024	2.0717	0.2968	2.1742	2.2247	-0.0454
Education level	2.6016	2.4422	0.1683	2.4551	2.5112	-0.0593
Technological access	3.1155	2.7888	0.3712	2.9944	2.9494	0.0511
General health	3.1434	2.8088	0.4002	3.0056	3.0225	-0.0202
Tiredness	2.7251	3.0837	-0.3022	2.8708	2.9438	-0.0615
Disability	2.5299	2.8486	-0.2423	2.6404	2.6685	-0.0214
Insomnia	2.9880	3.2311	-0.1741	3.0899	3.1124	-0.0161
Fatigue	2.8247	3.2351	-0.3409	3.0056	3.0337	-0.0233
Depression	2.5418	3.0996	-0.4375	2.7472	2.7753	-0.0220
Nervousness	2.5458	3.0598	-0.4062	2.7191	2.8090	-0.0710
Concentration	2.7171	3.0438	-0.2606	2.8483	2.8708	-0.0179
Stress	2.9761	3.2590	-0.2485	3.0449	3.1404	-0.0839
Trust in church	3.5777	3.3068	0.2223	3.5112	3.4607	0.0415

Trust in school	3.7251	3.2749	0.4239	3.5281	3.4494	0.0741
Trust in police	2.8526	2.7052	0.1329	2.8258	2.8090	0.0152
Trust in press	2.8167	2.7450	0.0676	2.7809	2.7303	0.0476
Trust in national government	2.9283	2.5618	0.3206	2.8483	2.6798	0.1474
Trust in local authorities	2.7530	2.5936	0.1681	2.6798	2.6573	0.0237

Sample Sizes:	**Control**	**Treated**
All	251	251
Matched	180	180
Unmatched	71	71
Discarded	0	0

Figure A.2: Covariate balancing before and after Propensity Score Matching

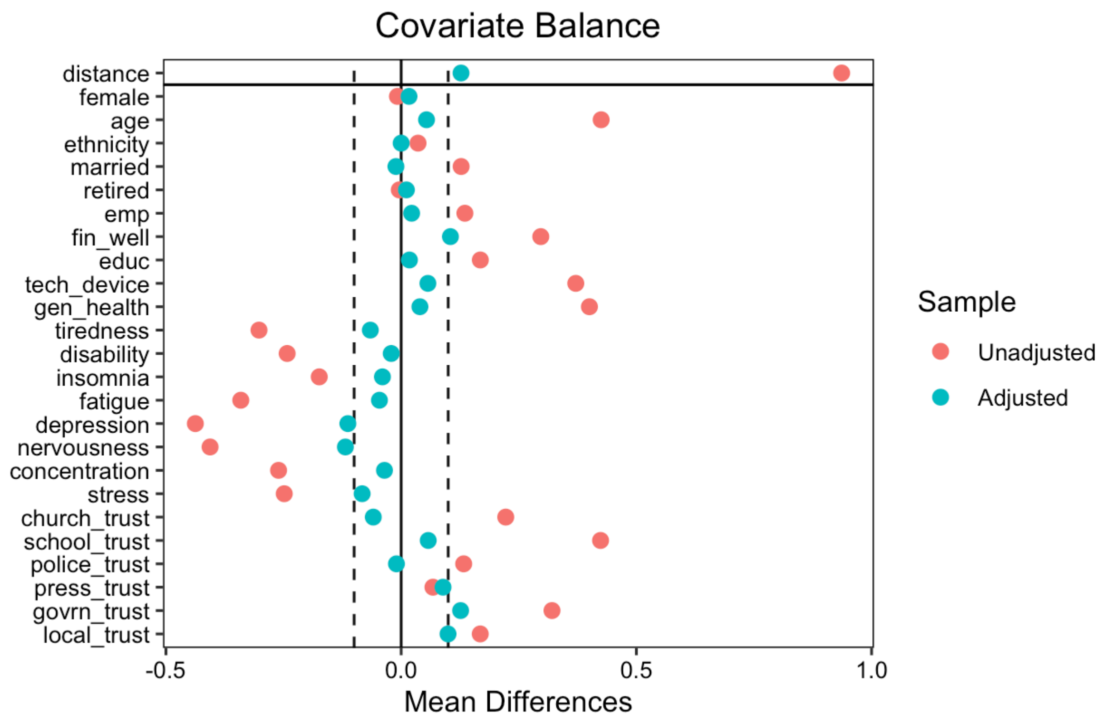


Table A.5: Balance summary for npCBGPS for the general model

Covariates	**Type**	**Unweighted correlation before npCBGPS**	**Weighted correlation after npCBGPS**
Ethnicity	Binary	0.0530	0.0099
Being retired	Binary	-0.0051	-0.0031
Financial well-being	Continuous	0.1762	0.0258
Education level	Continuous	0.1383	0.0218
Trust in press	Continuous	0.0031	-0.0047

Effective sample sizes:	
	Total
Unadjusted	502
Adjusted	484.61

Figure A.3: Covariate balancing before and after npCBGPS for the general model

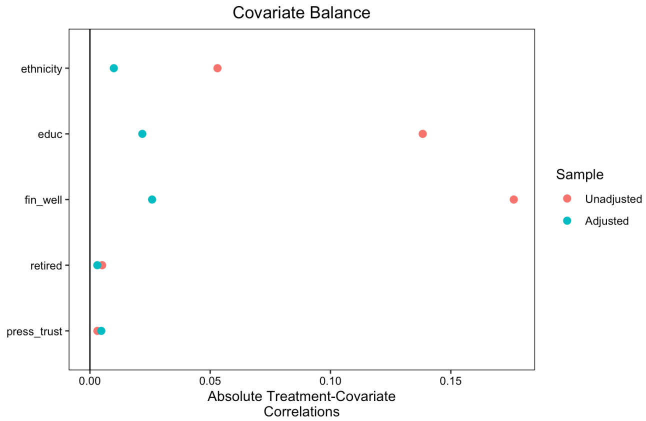


Table A.6: Balance summary for npCBGPS for low-severity mental health model (MH_{low})

Covariates	Type	Unweighted correlation before npCBGPS	Weighted correlation after npCBGPS
Being retired	Binary	-0.0453	-0.0006
Depression	Continuous	-0.1214	-0.0021

Effective sample sizes:

	Total
Unadjusted	168.
Adjusted	165.3

Figure A.4: Covariate balancing before and after npCBGPS for MH_{low} model

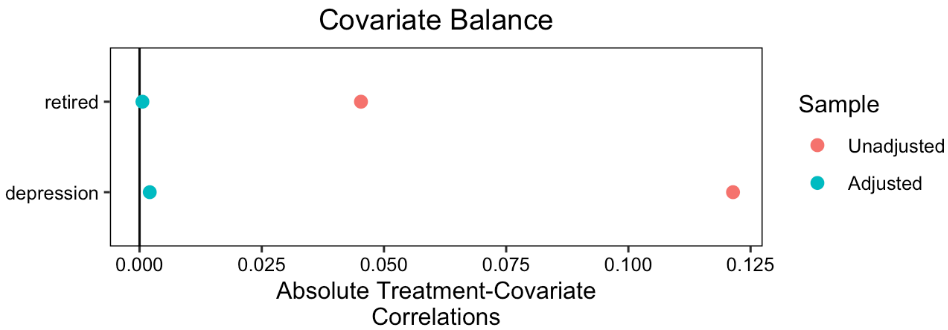


Table A.7: Balance summary for npCBGPS for moderate-severity mental health model (MH_{mod})

Covariates	Type	Unweighted correlation before npCBGPS	Weighted correlation after npCBGPS
Being married	Binary	0.0393	0.0031

Effective sample sizes:

	Total
Unadjusted	167.
Adjusted	166.75

Figure A.5: Covariate balancing before and after npCBGPS for MH_{mod} model

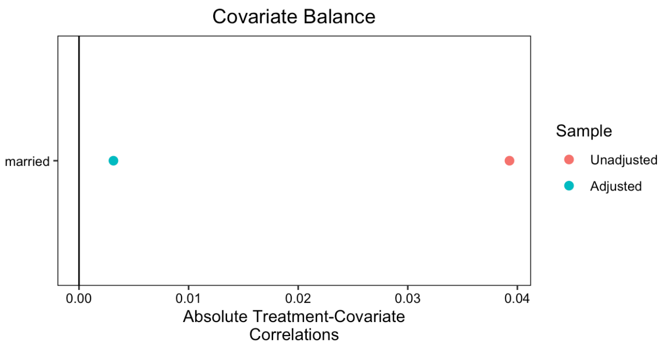


Table A.8: Balance summary for npCBGPS for high-severity mental health model (MH_{high})

Covariates	Type	Unweighted correlation before npCBGPS	Weighted correlation after npCBGPS
Employed	Binary	0.1269	0.0118
Fatigue	Continuous	-0.1515	-0.0345
Disability	Continuous	-0.0925	-0.0095
Trust in church	Continuous	0.1067	0.0078
Trust in local authorities	Continuous	0.1217	0.0220

Effective sample sizes:

	Total
Unadjusted	167.
Adjusted	156.1

Figure A.6: Covariate balancing before and after npCBGPS for MH_{high} model

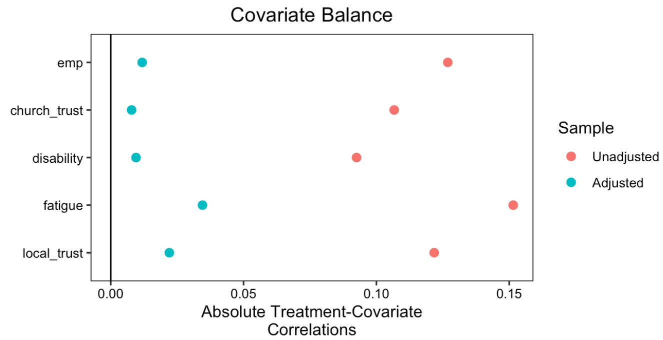


Table A.9: Balance summary for npCBGPS for the SEM group

Covariates	Type	Unweighted correlation before npCBGPS	Weighted correlation after npCBGPS
General health	Continuous	0.1569	0.0436

Effective sample sizes:

	Total
Unadjusted	160.
Adjusted	157.99

Figure A.7: Covariate balancing before and after npCBGPS for the SEM group

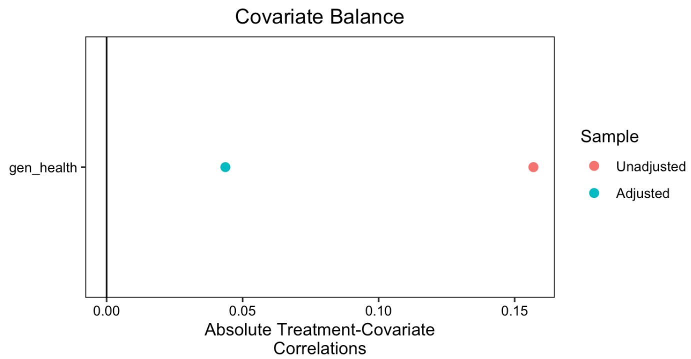


Table A.10: Balance summary for npCBGPS for the MSM group

Covariates	Type	Unweighted correlation before npCBGPS	Weighted correlation after npCBGPS
Being retired	Binary	0.1088	0.0061
General health	Continuous	-0.0039	0.0005

Effective sample sizes:

	Total
Unadjusted	135.
Adjusted	133.15

Figure A.8: Covariate balancing before and after npCBGPS for the MSM group

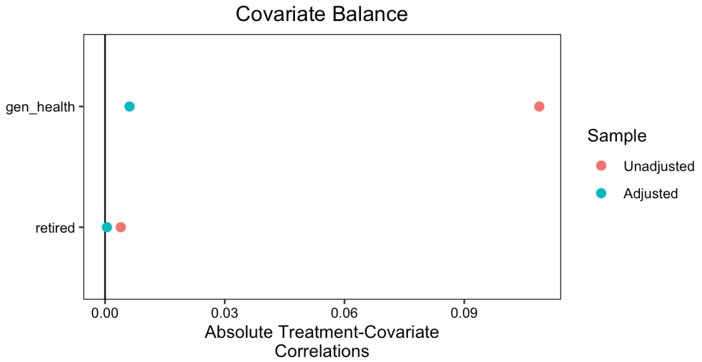


Table A.11: Balance summary for CBGPS for the SEM group

Covariates	Type	Unweighted correlation before npCBGPS	Weighted correlation after npCBGPS
General health	Continuous	0.1922	0.0407

Effective sample sizes:

	Total
Unadjusted	207.
Adjusted	202.74

Figure A.9: Covariate balancing before and after npCBGPS for the SEM group

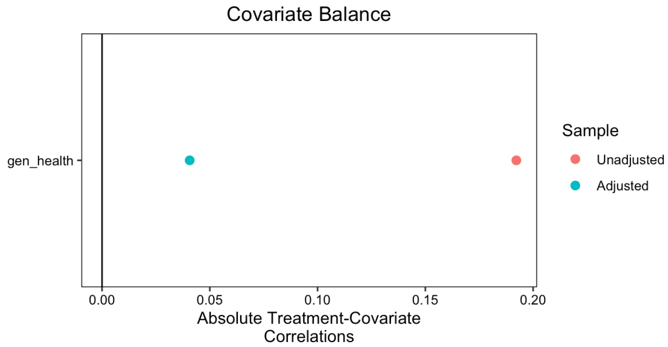


Table A.12: Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)
(1)	Gender	1.00																												
(2)	Age	0.16	1.00																											
(3)	Ethnicity	0.07	0.02	1.00																										
(4)	Being married	0.02	0.13	0.01	1.00																									
(5)	Employed status	-0.19	0.06	-0.03	0.11	1.00																								
(6)	Being retired	-0.06	0.32	-0.01	-0.02	0.32	1.00																							
(7)	Financial well–being	-0.17	0.09	-0.06	0.04	0.49	0.13	1.00																						
(8)	Education	0.05	-0.25	-0.11	0.06	0.20	-0.16	0.16	1.00																					
(9)	Technological access	0.03	-0.01	-0.01	0.16	0.22	-0.04	0.24	0.28	1.00																				
(10)	General health	-0.01	-0.01	0.00	0.01	0.16	-0.04	0.24	0.16	0.25	1.00																			
(11)	Tiredness	0.05	-0.07	0.05	-0.01	-0.19	-0.01	-0.13	-0.11	-0.15	-0.35	1.00																		
(12)	Disability	0.02	-0.14	0.08	-0.05	-0.21	-0.03	-0.19	-0.10	-0.18	-0.38	0.51	1.00																	
(13)	Insomnia	0.09	0.08	0.03	-0.06	-0.22	0.06	-0.24	-0.19	-0.16	-0.45	0.36	0.39	1.00																
(14)	Fatigue	0.13	-0.06	0.08	-0.01	-0.19	-0.02	-0.26	-0.06	-0.14	-0.44	0.42	0.51	0.61	1.00															
(15)	Depression	0.10	-0.06	0.04	-0.11	-0.25	0.03	-0.20	-0.10	-0.24	-0.54	0.47	0.51	0.62	0.67	1.00														
(16)	Anxiety	0.13	-0.04	0.02	-0.10	-0.16	-0.02	-0.15	-0.11	-0.21	-0.44	0.37	0.44	0.55	0.60	0.71	1.00													
(17)	Nervousness	0.08	-0.05	0.05	-0.12	-0.22	-0.04	-0.20	-0.12	-0.22	-0.44	0.40	0.45	0.53	0.57	0.68	0.64	1.00												
(18)	Concentration	0.01	-0.12	0.03	-0.06	-0.16	-0.06	-0.21	-0.03	-0.10	-0.41	0.40	0.50	0.48	0.62	0.61	0.55	0.59	1.00											
(19)	Stress	0.11	-0.11	0.07	-0.08	-0.17	-0.07	-0.16	-0.09	-0.17	-0.41	0.30	0.38	0.46	0.55	0.60	0.63	0.66	0.54	1.00										
(20)	Social inclusion	0.04	0.17	0.01	0.12	0.10	0.00	0.15	0.10	0.20	0.29	-0.25	-0.24	-0.25	-0.27	-0.32	-0.23	-0.27	-0.26	-0.26	1.00									
(21)	Subjective happiness	-0.05	0.02	0.01	0.08	0.19	0.01	0.24	0.07	0.20	0.60	-0.40	-0.41	-0.45	-0.47	-0.61	-0.52	-0.49	-0.43	-0.45	0.33	1.00								
(22)	Friendships	-0.01	0.17	0.04	0.18	0.24	-0.04	0.19	0.19	0.23	0.22	-0.18	-0.19	-0.21	-0.26	-0.27	-0.22	-0.25	-0.22	-0.19	0.35	0.33	1.00							
(23)	Social meetings	-0.01	0.08	0.02	0.03	0.05	0.02	0.06	0.03	0.11	0.21	-0.12	-0.13	-0.17	-0.20	-0.25	-0.23	-0.19	-0.18	-0.20	0.34	0.27	0.50	1.00						
(24)	Trust in church	0.08	0.04	0.08	0.03	-0.06	0.07	-0.07	-0.12	-0.04	0.05	-0.04	-0.03	0.02	0.07	0.00	0.02	0.04	-0.02	0.04	0.11	0.10	0.02	0.07	1.00					
(25)	Trust in school	-0.10	-0.05	-0.07	0.00	0.11	-0.04	0.15	0.15	0.14	0.07	-0.10	-0.08	-0.14	-0.12	-0.11	-0.05	-0.11	-0.08	-0.02	0.17	0.12	0.16	0.12	0.35	1.00				
(26)	Trust in police	-0.03	-0.04	-0.07	0.01	-0.01	0.03	-0.03	-0.02	-0.02	0.02	0.01	0.02	-0.05	-0.01	0.02	0.02	0.00	0.01	0.03	0.07	0.05	0.08	0.04	0.38	0.42	1.00			
(27)	Trust in press	0.06	0.00	-0.04	-0.07	0.01	0.04	0.03	0.07	0.01	-0.01	-0.02	-0.03	0.03	0.03	0.02	-0.01	0.04	0.01	0.07	0.08	0.05	0.04	0.03	0.20	0.32	0.30	1.00		
(28)	Trust in national government	0.03	0.21	-0.04	-0.03	-0.02	0.12	0.06	0.02	0.04	0.06	-0.03	-0.06	-0.01	0.00	0.00	-0.01	0.04	-0.04	-0.04	0.20	0.07	0.11	0.07	0.15	0.32	0.30	0.41	1.00	
(29)	Trust in local authorities	0.02	0.09	0.00	-0.08	-0.05	0.08	0.01	-0.02	0.01	0.04	-0.07	-0.04	-0.03	-0.01	0.00	-0.01	0.01	-0.05	0.01	0.12	0.07	0.07	0.06	0.26	0.30	0.47	0.43	0.62	1.00

Table A.13: Ordered Probit results for the unweighted general model

	(1)	(2)	(3)	(4)
Social capital	0.399*** (0.071)	0.395*** (0.071)		
Social capital$_{high}$			0.521*** (0.110)	0.515*** (0.110)
Trust in institutions	0.112* (0.059)	0.112* (0.059)	0.107* (0.059)	0.105* (0.059)
SE × MH		0.035 (0.070)		
SE$_{high}$ × MH				0.071 (0.115)
Gender	0.077 (0.127)	0.075 (0.127)	0.101 (0.127)	0.097 (0.127)
Age	-0.080* (0.044)	-0.078* (0.044)	-0.065 (0.044)	-0.064 (0.044)
Race	0.074 (0.136)	0.079 (0.136)	0.087 (0.136)	0.089 (0.136)
Education	-0.155** (0.060)	-0.155** (0.060)	-0.130** (0.060)	-0.130** (0.060)
Financial well-being	0.113** (0.051)	0.113** (0.051)	0.119** (0.051)	0.118** (0.051)
General health	0.548*** (0.073)	0.545*** (0.073)	0.565*** (0.073)	0.564*** (0.073)
Mental health	-0.659*** (0.071)	-0.660*** (0.071)	-0.647*** (0.070)	-0.682*** (0.091)
Observations	502	502	502	502
1|2	-0.599* (0.344)	-0.600* (0.344)	-0.106 (0.324)	-0.112 (0.324)
2|3	0.449 (0.344)	0.450 (0.344)	0.921*** (0.327)	0.919*** (0.327)
3|4	2.090*** (0.352)	2.090*** (0.352)	2.537*** (0.339)	2.534*** (0.339)

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Exact p-values available upon request.*

Table A.14: OLS results for the unweighted general model

	(1)	(2)	(3)	(4)
Constant	2.063*** (0.218)	2.070*** (0.218)	1.765*** (0.213)	1.772*** (0.213)
Social capital	0.239*** (0.043)	0.236*** (0.043)		
Social capital$_{high}$			0.311*** (0.065)	0.311*** (0.065)
Mental health	-0.387*** (0.043)	-0.389*** (0.043)	-0.385*** (0.043)	-0.436*** (0.05)
Trust in institutions	0.064 (0.040)	0.062 (0.040)	0.060 (0.040)	0.058 (0.040)
SE × MH		0.052 (0.042)		
SE$_{high}$ × MH				0.099 (0.068)
Gender	0.041 (0.076)	0.038 (0.076)	0.058 (0.078)	0.052 (0.078)
Age	-0.050* (0.026)	-0.048* (0.026)	-0.042 (0.026)	-0.040 (0.026)
Race	0.053 (0.080)	0.060 (0.080)	0.062 (0.082)	0.066 (0.082)
Education	-0.084** (0.036)	-0.083** (0.036)	-0.070* (0.036)	-0.069* (0.036)
Financial well-being	0.062** (0.030)	0.061** (0.030)	0.067** (0.031)	0.065** (0.031)
General health	0.353*** (0.050)	0.348*** (0.050)	0.370*** (0.049)	0.366*** (0.049)
Observations	502	502	502	502
Multiple R^2	0.5062	0.5038	0.4951	0.4975
Adjusted R^2	0.4971	0.4979	0.4859	0.4873
F-statistic	56.03***	50.69***	53.61***	48.61***

The Breusch-Pagan test was applied to all OLS models to assess the presence of heteroskedasticity. As the test returned p-values below 0.05, robust standard errors were reported in brackets.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Exact p-values available upon request.*

Table A.15: Subsample Ordered Probit results without weighting balance

	MH_{low}	MH_{mod}	MH_{high}
Social capital	0.211 (0.129)	0.487*** (0.132)	0.384*** (0.082)
Trust in institutions	-0.058 (0.117)	0.109 (0.118)	0.119 (0.063)
Gender	0.063 (0.211)	0.289 (0.228)	-0.228 (0.175)
Age	0.072 (0.077)	-0.064 (0.082)	-0.203*** (0.055)
Race	0.052 (0.244)	-0.093 (0.238)	0.088 (0.181)
Education	-0.074 (0.111)	-0.128 (0.106)	-0.220** (0.075)
Financial well-being	0.021 (0.093)	0.110 (0.088)	0.154* (0.067)
General health	0.579*** (0.184)	0.841*** (0.132)	0.630*** (0.070)
Observations	168	167	167
1|2	-0.032 (0.832)	-0.231 (0.595)	-0.333 (0.536)
2|3	0.499 (0.814)	1.354** (0.601)	0.638 (0.540)
3|4	1.946** (0.823)	3.323*** (0.632)	2.004*** (0.550)

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Exact p-values available upon request.*

Table A.16: Subsample OLS results without weighting balance

	MH_{low}	MH_{mod}	MH_{high}
Constant	2.433*** (0.461)	1.727*** (0.296)	1.933*** (0.398)
Social capital	0.130 (0.084)	0.246*** (0.066)	0.277*** (0.082)
Trust in institutions	0.004 (0.068)	0.055 (0.061)	0.085 (0.063)
Gender	0.028 (0.132)	0.153 (0.117)	-0.146 (0.175)
Age	0.032 (0.043)	-0.030 (0.042)	-0.152*** (0.055)
Race	0.060 (0.154)	-0.038 (0.122)	0.071 (0.181)
Education	-0.038 (0.062)	-0.064 (0.054)	-0.152** (0.075)
Financial well-being	0.009 (0.057)	0.056 (0.045)	0.110 (0.067)
General health	0.283*** (0.101)	0.440*** (0.061)	0.459*** (0.070)
Observations	168	167	167
Multiple R^2	0.09749	0.3721	0.3395
Adjusted R^2	0.05208	0.3403	0.306
F-statistic	2.147**	11.71***	10.15***

The Breusch-Pagan test was applied to all OLS models to assess the presence of heteroskedasticity. As the test returned p-values below 0.05, robust standard errors were reported in brackets.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Exact p-values available upon request.*

Table A.17: Cluster Ordered Probit results without weighting balance

	SEM	MSM	CAPS
Social capital	0.270* (0.143)	0.701*** (0.150)	0.356*** (0.110)
Mental health	-0.524*** (0.153)	-0.793*** (0.159)	-0.648*** (0.124)
Trust in institutions	-0.018 (0.129)	-0.024 (0.134)	0.192** (0.081)
Gender	0.114 (0.217)	0.350 (0.305)	-0.043 (0.202)
Age	0.059 (0.083)	-0.035 (0.093)	-0.164** (0.070)
Race	-0.266 (0.319)	0.084 (0.267)	0.195 (0.208)
Education	-0.036 (0.106)	-0.301** (0.133)	-0.172* (0.097)
Financial well-being	0.014 (0.099)	0.208** (0.101)	0.103 (0.081)
General health	0.560*** (0.169)	0.267* (0.146)	0.751*** (0.108)
Observations	160	136	206
1|2	-0.666 (0.838)	-1.102 (0.723)	-0.495 (0.512)
2|3	0.713 (0.778)	-0.221 (0.716)	0.652 (0.519)
3|4	2.143*** (0.789)	1.638** (0.733)	2.479*** (0.532)

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Exact p-values available upon request.*

Table A.18: Cluster OLS results without weighting balance

	SEM	MSM	CAPS
Constant	2.268*** (0.401)	2.474*** (0.424)	1.870*** (0.305)
Social capital	0.146** (0.073)	0.403*** (0.084)	0.201*** (0.064)
Mental health	-0.283*** (0.077)	-0.447*** (0.088)	-0.365*** (0.068)
Trust in institutions	0.002 (0.065)	-0.016 (0.078)	0.104** (0.047)
Gender	0.043 (0.112)	0.172 (0.183)	-0.010 (0.121)
Age	0.026 (0.042)	-0.026 (0.054)	-0.093** (0.041)
Race	-0.076 (0.150)	0.029 (0.159)	0.133 (0.123)
Education	-0.020 (0.054)	-0.153** (0.077)	-0.086 (0.057)
Financial well-being	-0.006 (0.050)	0.111* (0.058)	0.061 (0.049)
General health	0.291*** (0.086)	0.167* (0.087)	0.461*** (0.060)
Observations	160	136	206
Multiple R^2	0.2205	0.43	0.5289
Adjusted R^2	0.1737	0.3889	0.5074
F-statistic	4.714***	10.48***	24.58***

The Breusch-Pagan test was applied to all OLS models to assess the presence of heteroskedasticity. As the test returned p-values below 0.05, robust standard errors were reported in brackets.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Exact p-values available upon request.*

Table A.19: OLS results for the weighted general model

	(1)	(2)	(3)	(4)
Constant	2.079***	2.086***	2.075***	2.092***
	(0.213)	(0.213)	(0.284)	(0.071)
Social capital	0.235***	0.233***		
	(0.044)	(0.044)		
Social capital$_{high}$			0.247***	0.244***
			(0.072)	(0.071)
Mental health	-0.386***	-0.387***	-0.420***	-0.483***
	(0.044)	(0.044)	(0.047)	(0.062)
Trust in institutions	0.065	0.064	0.052	0.049
	(0.040)	(0.040)	(0.046)	(0.047)
SE × MH		0.045		
		(0.044)		
SE$_{high}$ × MH				0.122
				(0.078)
Gender	0.024	0.022	0.067*	0.057
	(0.078)	(0.078)	(0.094)	(0.094)
Age	-0.042	-0.040*	-0.088***	-0.086***
	(0.026)	(0.026)	(0.033)	(0.033)
Race	0.023	0.026	0.031	0.033
	(0.080)	(0.080)	(0.103)	(0.104)
Education level	-0.077*	-0.076**	-0.100**	-0.102**
	(0.036)	(0.036)	(0.043)	(0.043)
Financial well-being	0.058*	0.057**	0.087**	0.081**
	(0.031)	(0.031)	(0.036)	(0.036)
General health	0.350***	0.347***	0.348***	0.348***
	(0.050)	(0.051)	(0.058)	(0.058)
Observations	502	502	502	502
Multiple R^2	0.4923	0.4936	0.4697	0.4735
Adjusted R^2	0.483	0.4833	0.456	0.4584
F-statistic	53***	47.86***	34.44***	31.39***

The Breusch-Pagan test was applied to all OLS models to assess the presence of heteroskedasticity. As the test returned p-values below 0.05, robust standard errors were reported in brackets.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Exact p-values available upon request.*

Table A.20: Subsample OLS results with weighting balance

	MH$_{low}$	MH$_{mod}$	MH$_{high}$
Constant	2.328***	1.730***	1.941***
	(0.465)	(0.296)	(0.390)
Social capital	0.087	0.243***	0.269***
	(0.080)	(0.066)	(0.081)
Trust in institutions	-0.003	0.056	0.100
	(0.070)	(0.061)	(0.063)
Gender	0.046	0.149	-0.136
	(0.138)	(0.117)	(0.178)
Age	0.038	-0.032	-0.178***
	(0.040)	(0.042)	(0.053)
Race	0.091	-0.041	0.165
	(0.158)	(0.122)	(0.179)
Education level	-0.015	-0.063	-0.158**
	(0.062)	(0.054)	(0.074)
Financial well-being	0.002	0.056	0.130*
	(0.058)	(0.045)	(0.067)
General health	0.270**	0.442***	0.447***
	(0.104)	(0.061)	(0.070)
Observations	168	167	167
Multiple R^2	0.07586	0.3711	0.3349
Adjusted R^2	0.02936	0.3393	0.3012
F-statistic	1.631	11.66***	9.944***

The Breusch-Pagan test was applied to all OLS models to assess the presence of heteroskedasticity. As the test returned p-values below 0.05, robust standard errors were reported in brackets.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Exact p-values available upon request.*

Table A.21: Cluster OLS results with weighting balance

	SEM	MSM	CAPS
Constant	2.212*** (0.397)	2.443*** (0.429)	1.889*** (0.302)
Social capital	0.147** (0.072)	0.391*** (0.085)	0.196*** (0.062)
Mental health	-0.287*** (0.077)	-0.437*** (0.087)	-0.371*** (0.068)
Trust in institutions	0.004 (0.064)	-0.032 (0.080)	0.099** (0.047)
Gender	0.040 (0.111)	0.162 (0.186)	0.016 (0.121)
Age	0.027 (0.042)	-0.021 (0.055)	-0.095** (0.041)
Race	-0.082 (0.149)	0.028 (0.161)	0.100 (0.124)
Education level	-0.013 (0.054)	-0.154** (0.078)	-0.092 (0.056)
Financial well-being	-0.001 (0.049)	0.110* (0.059)	0.063 (0.048)
General health	0.299*** (0.085)	0.182** (0.088)	0.465*** (0.059)
Observations	160	136	206
Multiple R^2	0.2241	0.4095	0.5218
Adjusted R^2	0.1775	0.367	0.5
F-statistic	4.812***	9.633***	23.89***

The Breusch-Pagan test was applied to all OLS models to assess the presence of heteroskedasticity. As the test returned p-values below 0.05, robust standard errors were reported in brackets.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Exact p-values available upon request.*

Table A.22: General estimates regression for interaction model with weighting balance

Constant	2.137*** (0.204)
Social capital	0.224*** (0.040)
Mental health	-0.386*** (0.049)
SC^2	-0.070 (0.047)
Trust in institutions	0.062* (0.034)
$SC \cdot MH$	0.047 (0.040)
$SC^2 \cdot MH$	0.002 (0.047)
Observations	502
Controls	Yes
Multiple R-squared	0.4959
Adjusted R-squared	0.4835
F-statistic	40.09***

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Exact p-values available upon request.*

Table A.23: Subsample estimates regression for interaction model with weighting balance

Constant	2.296*** (0.231)
Social capital	0.147** (0.071)
MH_{mod}	-0.254** (0.107)
MH_{high}	-0.689*** (0.116)
SC^2	-0.040 (0.084)
Trust in institutions	0.056 (0.036)
$\mathrm{SC} \cdot \mathrm{MH}_{mod}$	0.100 (0.100)
$\mathrm{SC} \cdot \mathrm{MH}_{high}$	0.090 (0.097)
$\mathrm{SC}^2 \cdot \mathrm{MH}_{mod}$	-0.085 (0.123)
$\mathrm{SC}^2 \cdot \mathrm{MH}_{high}$	-0.030 (0.116)
Observations	502
Controls	Yes
Multiple R-squared	0.4621
Adjusted R-squared	0.4455
F-statistic	27.84***

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Exact p-values available upon request.*

Table A.24: Cluster estimates regression for interaction model with weighting balance

Constant	1.893*** (0.233)
Social capital	0.090 (0.076)
MSM	-0.200* (0.121)
CAPS	-0.437*** (0.110)
SC^2	-0.040** (0.093)
Trust in institutions	0.051 (0.036)
$\mathrm{SC} \cdot \mathrm{MSM}$	0.319*** (0.114)
$\mathrm{SC} \cdot \mathrm{CAPS}$	0.048 (0.100)
$\mathrm{SC}^2 \cdot \mathrm{MSM}$	-0.287* (0.150)
$\mathrm{SC}^2 \cdot \mathrm{CAPS}$	-0.015 (0.118)
Observations	502
Controls	Yes
Multiple R-squared	0.4381
Adjusted R-squared	0.4207
F-statistic	25.26***

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Exact p-values available upon request.*

Figure A.10: Average marginal effects (AME) for the general model

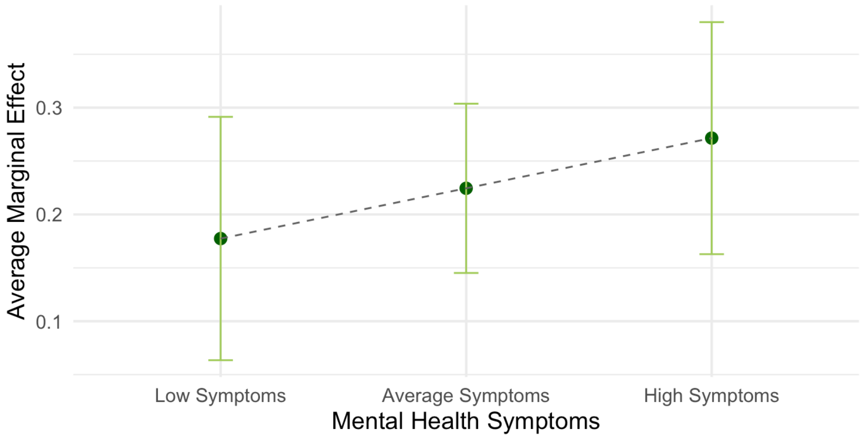


Figure A.11: Average marginal effects (AME) for the subsample model

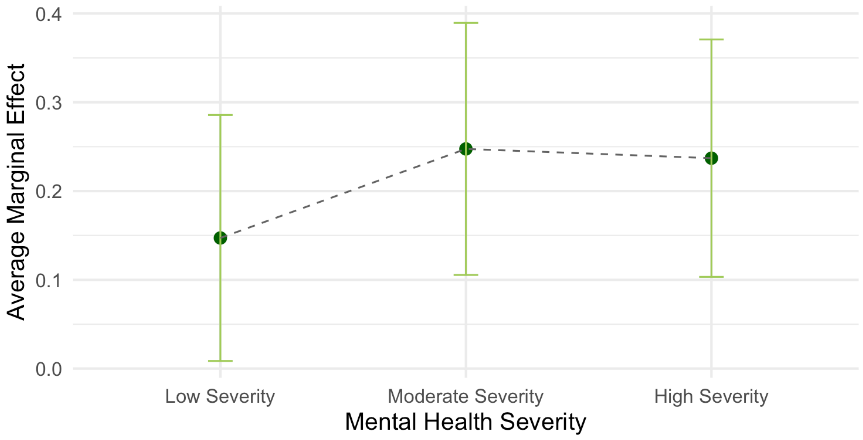


Figure A.12: Average marginal effects (AME) for the cluster model

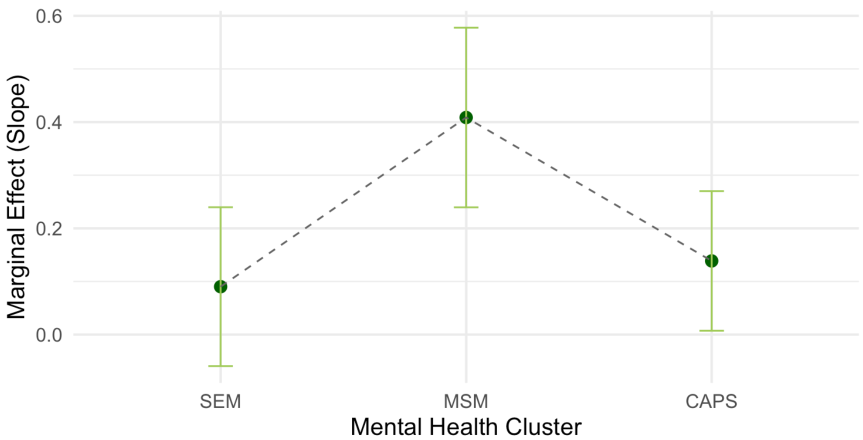
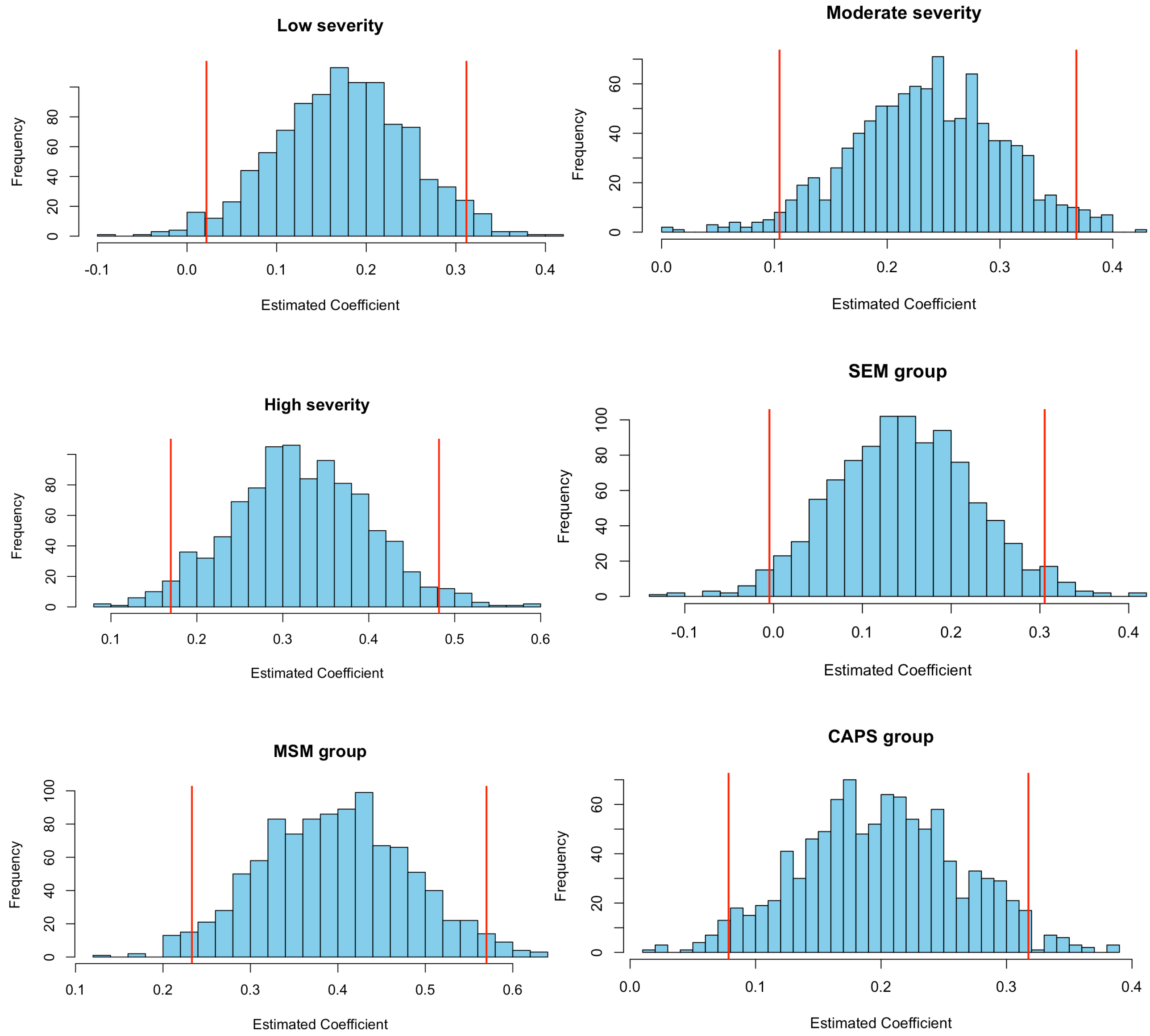


Figure A.13: Bootstrap distributions of social capital coefficients across subgroups (1,000 iterations)



Appendix B

Chapter 2 Appendix

Missing values

In this study, missing values represent a substantial loss of information. We identified four types of missing data as outlined in the GSS's codebook (2021; 2022). "Inapplicable" responses occur when a respondent does not encounter a question due to structural factors, such as being assigned to a specific ballot that excludes certain questions, or personal factors, such as when an unmarried respondent is marked as inapplicable for spouse–related inquiries. The "Don't know/Cannot Choose" category is used when respondents indicate their inability or unwillingness to provide an answer, reflecting either uncertainty about the question. The "No Answer" option is assigned when respondents explicitly refuse to answer a question, indicating a decision not to engage with that. Lastly, "Skipped on Web" describes instances where respondents bypass questions while completing the survey online, indicating a deliberate choice not to provide an answer.

As presented in the table below, the majority of missing values fall under the "Inapplicable" category, due to specific questions not being administered to certain ballots or being irrelevant to particular respondents. For instance, respondents who indicate "Never used" for lifetime crack/cocaine use and drug injection are not asked follow–up questions about these drug behaviors. In such cases, both subsequent variables on crack/cocaine use and drug injection over time are coded as "Inapplicable". We interpret these "Inapplicable" responses as equivalent to "Never used" for both drug use–related variables, thus preserving a substantial portion of missing data.

Table B.1: Specifications for missing values

	Inapplicable	*Don't know / Cannot Choose*	*No answer*	*Skipped on web*
Sex	19		71	2
Age	226		114	
Race	54			
Hispanic	21	9	9	10
Education	20		49	
Financial well–being		7	4	10
Subjective happiness		5	1	16
Living place at 16yo		1		2
Living with both parents at 16yo		1	4	1
Family income at 16yo	71	157	8	16
Social satisfaction	380	6	17	28
Social trust	784	6	1	2
Lifetime crack/cocaine use	2,650	26	14	20
Crack/cocaine use over time	2,676	3	36	
Lifetime injection drug use	2,650	36	17	27
Injection drug use over time	2,713	3	19	3

Table B.2: Correlation matrix for crack/cocaine use dataset

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1)	Male	1.000																				
(2)	Age	0.024	1.000																			
(3)	Age^2	0.027	0.987	1.000																		
(4)	White	0.017	0.157	0.157	1.000																	
(5)	Black	–0.039	–0.092	–0.092	–0.695	1.000																
(6)	Other	0.018	–0.118	–0.117	–0.633	–0.116	1.000															
(7)	Hispanic	–0.036	–0.208	–0.199	–0.196	–0.083	0.360	1.000														
(8)	Years of education	0.044	0.029	0.013	0.084	–0.087	–0.023	–0.129	1.000													
(9)	Current family income	0.113	0.002	–0.001	0.112	–0.115	–0.031	–0.091	0.326	1.000												
(10)	Subjective happiness	0.007	0.011	0.004	0.015	–0.046	0.029	0.033	0.056	0.163	1.000											
(11)	Living in a small town at 16yo	0.002	–0.011	–0.008	0.054	–0.057	–0.013	–0.021	–0.072	–0.032	0.019	1.000										
(12)	Living in a large town at 16yo	0.014	–0.027	–0.034	–0.204	0.181	0.087	0.109	0.029	–0.006	0.009	–0.306	1.000									
(13)	Living in a suburb at 16yo	0.016	–0.002	–0.004	0.044	–0.051	–0.006	–0.062	0.138	0.117	–0.009	–0.313	–0.206	1.000								
(14)	Living in open country/farm at 16yo	0.026	0.098	0.102	0.123	–0.083	–0.080	–0.077	–0.082	–0.046	0.002	–0.294	–0.193	–0.198	1.000							
(15)	Living with both parents at 16yo	0.055	0.184	0.183	0.119	–0.154	0.002	–0.057	0.155	0.149	0.019	0.001	–0.052	0.071	0.054	1.000						
(16)	Separated or divorced parents at 16yo	–0.017	–0.175	–0.176	–0.041	0.053	–0.001	0.037	–0.072	–0.082	–0.015	–0.010	0.021	–0.043	–0.044	–0.730	1.000					
(17)	One or both parents died at 16yo	–0.057	0.033	0.029	–0.043	0.057	–0.002	–0.010	–0.052	–0.037	0.041	0.001	0.019	–0.031	–0.008	–0.397	–0.078	1.000				
(18)	Family income at 16yo	–0.007	–0.057	–0.053	0.163	–0.096	–0.121	–0.122	0.151	0.220	0.005	–0.040	–0.012	0.148	–0.091	0.143	–0.072	–0.065	1.000			
(19)	Crack/cocaine use	0.012	–0.045	–0.053	–0.026	0.049	–0.016	–0.020	–0.087	–0.111	–0.069	–0.007	0.025	0.011	–0.003	–0.104	0.088	0.015	0.006	1.000		
(20)	Social satisfaction	0.030	0.050	0.052	0.017	–0.011	–0.012	0.005	0.076	0.197	0.412	0.009	–0.004	0.026	–0.019	0.030	–0.022	0.007	0.011	–0.067	1.000	
(21)	Social trust	0.084	0.148	0.149	0.154	–0.154	–0.046	–0.137	0.253	0.214	0.124	–0.026	–0.006	0.077	–0.031	0.114	–0.080	–0.010	0.095	–0.065	0.144	1.000

Table B.3: Correlation matrix for injection drug use dataset

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
(1)	Male	1.000																				
(2)	Age	0.023	1.000																			
(3)	Age^2	0.027	0.986	1.000																		
(4)	White	0.014	0.154	0.154	1.000																	
(5)	Black	–0.037	–0.091	–0.091	–0.695	1.000																
(6)	Other	0.020	–0.114	–0.114	–0.634	–0.116	1.000															
(7)	Hispanic	–0.036	–0.207	–0.198	–0.193	–0.082	0.355	1.000														
(8)	Years of education	0.041	0.028	0.012	0.080	–0.084	–0.020	–0.128	1.000													
(9)	Current family income	0.114	0.003	0.001	0.113	–0.115	–0.032	–0.094	0.328	1.000												
(10)	Subjective happiness	0.006	0.012	0.004	0.016	–0.046	0.027	0.031	0.055	0.163	1.000											
(11)	Living in a small town at 16yo	–0.002	–0.012	–0.009	0.056	–0.058	–0.015	–0.018	–0.074	–0.030	0.019	1.000										
(12)	Living in a large town at 16yo	0.018	–0.024	–0.032	–0.203	0.178	0.089	0.108	0.028	–0.009	0.009	–0.306	1.000									
(13)	Living in a suburb at 16yo	0.016	–0.003	–0.005	0.042	–0.050	–0.005	–0.062	0.140	0.117	–0.011	–0.314	–0.205	1.000								
(14)	Living in open country/farm at 16yo	0.025	0.097	0.101	0.121	–0.082	–0.079	–0.077	–0.082	–0.045	0.005	–0.295	–0.193	–0.198	1.000							
(15)	Living with both parents at 16yo	0.054	0.185	0.184	0.119	–0.154	0.001	–0.058	0.156	0.152	0.022	–0.001	–0.053	0.075	0.053	1.000						
(16)	Separated or divorced parents at 16yo	–0.018	–0.176	–0.177	–0.041	0.053	–0.001	0.039	–0.075	–0.083	–0.016	–0.010	0.024	–0.044	–0.045	–0.733	1.000					
(17)	One or both parents died at 16yo	–0.057	0.030	0.027	–0.045	0.059	–0.002	–0.009	–0.050	–0.040	0.042	0.002	0.020	–0.035	–0.007	–0.395	–0.078	1.000				
(18)	Family income at 16yo	–0.007	–0.057	–0.053	0.164	–0.096	–0.123	–0.123	0.153	0.219	0.004	–0.041	–0.013	0.148	–0.090	0.145	–0.074	–0.066	1.000			
(19)	Injection drug use	–0.011	–0.054	–0.056	–0.013	0.017	–0.001	–0.024	–0.071	–0.083	–0.070	0.018	0.016	0.012	–0.053	–0.055	0.023	0.026	–0.020	1.000		
(20)	Social satisfaction	0.030	0.052	0.053	0.015	–0.009	–0.011	0.000	0.075	0.197	0.412	0.009	–0.004	0.026	–0.017	0.033	–0.023	0.008	0.011	–0.053	1.000	
(21)	Social trust	0.081	0.148	0.148	0.152	–0.152	–0.046	–0.138	0.255	0.215	0.122	–0.028	–0.005	0.076	–0.029	0.117	–0.081	–0.012	0.096	–0.031	0.144	1.000

Table B.4: OLS regressions comparing original and collapsed specifications of crack/cocaine use

Outcome variable: crack/cocaine use	**Original**			**Collapsed**		
	β	*SE*	*p*	*β*	*SE*	*p*
Constant	0.233	0.047	0.000***	0.211	0.039	0.000***
Male	0.016	0.012	0.181	0.016	0.010	0.113
Age	–0.001	0.000	0.081*	–0.000	0.000	0.141
Age^2	–0.000	0.000	0.006***	–0.056	0.017	0.000***
White	0.007	0.022	0.760	0.005	0.018	0.775
Black	0.024	0.028	0.386	0.018	0.023	0.431
Hispanic	–0.030	0.021	0.144	–0.029	0.017	0.097*
Years of education	–0.007	0.003	0.007***	–0.007	0.002	0.002***
Current family income	–0.029	0.007	0.000***	–0.026	0.006	0.000***
Subjective happiness	–0.024	0.009	0.007***	–0.020	0.008	0.007***
Living in a small town at 16yo	0.014	0.017	0.415	0.014	0.015	0.338
Living in a large town at 16yo	0.028	0.020	0.169	0.031	0.017	0.070*
Living in suburb at 16yo	0.032	0.020	0.107	0.034	0.017	0.044**
Living in open country/on a farm at 16yo	0.019	0.021	0.365	0.017	0.017	0.319
Living with both parents at 16yo	–0.056	0.029	0.057*	–0.050	0.025	0.044**
Divorced or separated parents at 16yo	0.017	0.033	0.595	0.016	0.027	0.549
One or both parents died at 16yo	–0.021	0.041	0.603	–0.020	0.034	0.567
Family income at 16yo	0.014	0.007	0.038**	0.012	0.006	0.042**
Social satisfaction	0.233	0.047	0.000***	0.211	0.039	0.000***
Social trust	0.016	0.012	0.181	0.016	0.010	0.113
F statistic		5.601***			6.405***	
R^2		0.02602			0.03043	

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table B.5: OLS regressions comparing original and collapsed specifications of drug injection

Outcome variable: injection drug use	**Original**			**Collapsed**		
	β	*SE*	*p*	*β*	*SE*	*p*
Constant	0.269	0.044	0.001***	0.212	0.036	0.000***
Male	–0.001	0.011	0.936	0.000	0.009	0.997
Age	–0.001	0.000	0.002***	–0.001	0.000	0.005***
Age^2	–0.000	0.000	0.332	–0.000	0.000	0.261
White	0.001	0.021	0.960	–0.001	0.017	0.943
Black	–0.018	0.026	0.501	–0.017	0.021	0.431
Hispanic	–0.051	0.019	0.008***	–0.042	0.016	0.007***
Years of education	–0.007	0.002	0.004***	–0.006	0.002	0.004***
Current family income	–0.019	0.006	0.004***	–0.015	0.005	0.004***
Subjective happiness	–0.026	0.008	0.002***	–0.021	0.007	0.003***
Living in a small town at 16yo	0.004	0.016	0.803	0.005	0.013	0.733
Living in a large town at 16yo	0.011	0.019	0.561	0.013	0.015	0.392
Living in suburb at 16yo	0.015	0.019	0.410	0.015	0.015	0.327
Living in open country/on a farm at 16yo	–0.040	0.019	0.038**	–0.033	0.016	0.040**
Living with both parents at 16yo	–0.053	0.028	0.059*	–0.034	0.023	0.128
Divorced or separated parents at 16yo	–0.051	0.031	0.100*	–0.029	0.025	0.253
One or both parents died at 16yo	–0.025	0.038	0.507	–0.002	0.031	0.959
Family income at 16yo	–0.004	0.006	0.519	–0.003	0.005	0.583
Social satisfaction	0.269	0.044	0.000***	0.212	0.036	0.000***
Social trust	–0.001	0.011	0.936	0.000	0.009	0.997
F statistic		4.103***			4.001***	
R^2		0.01776			0.01718	

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table B.6: The Ordered Probit estimates including both IVs as regressors in the initial model

	Crack/cocaine use						Injection drug use					
	Model 1 (without SH)			Model 2 (with SH)			Model 1 (without SH)			Model 2 (with SH)		
	β	*SE*	*p*	*β*	*SE*	*p*	*β*	*SE*	*p*	*β*	*SE*	*p*
Male	0.177	0.084	0.035**	0.173	0.084	0.045**	0.034	0.104	0.745	0.032	0.104	0.757
Age	–0.006	0.003	0.052*	–0.006	0.003	0.044**	–0.006	0.003	0.068*	–0.006	0.003	0.061*
Age^2	–0.001	0.000	0.000***	–0.001	0.000	0.000***	–0.000	0.000	0.089*	–0.000	0.000	0.078*
White	0.041	0.162	0.798	0.037	0.161	0.827	–0.060	0.185	0.747	–0.068	0.185	0.714
Black	0.114	0.190	0.549	0.103	0.189	0.600	–0.302	0.237	0.202	–0.322	0.238	0.175
Hispanic	–0.290	0.163	0.075*	–0.278	0.163	0.086*	–0.492	0.205	0.016**	–0.470	0.205	0.022**
Years of education	–0.064	0.018	0.000***	–0.067	0.018	0.001***	–0.061	0.023	0.008***	–0.064	0.023	0.006***
Current family income	–0.217	0.049	0.000***	–0.204	0.050	0.000***	–0.166	0.059	0.005***	–0.151	0.060	0.012**
Subjective happiness				–0.152	0.067	0.032**				–0.172	0.086	0.044**
Living in a small town at 16yo	0.192	0.132	0.145	0.192	0.131	0.160	0.088	0.149	0.554	0.095	0.150	0.526
Living in a large town at 16yo	0.347	0.147	0.019**	0.350	0.148	0.018***	0.185	0.170	0.279	0.194	0.171	0.257
Living in suburb at 16yo	0.375	0.145	0.010**	0.377	0.145	0.013***	0.217	0.168	0.198	0.219	0.169	0.194
Living in open country/on a farm at 16yo	0.165	0.152	0.277	0.167	0.151	0.297	–0.598	0.253	0.018**	–0.576	0.252	0.022**
Living with both parents at 16yo	–0.322	0.160	0.044**	–0.312	0.159	0.066*	–0.263	0.203	0.195	–0.245	0.204	0.230
Divorced or separated parents at 16yo	0.100	0.171	0.558	0.119	0.170	0.513	–0.137	0.223	0.538	–0.120	0.224	0.591
One or both parents died at 16yo	–0.137	0.244	0.573	–0.097	0.244	0.696	–0.064	0.288	0.825	–0.023	0.291	0.937
Family income at 16yo	0.113	0.045	0.012**	0.112	0.045	0.021**	–0.000	0.060	0.999	0.001	0.060	0.990
Social satisfaction	–0.076	0.043	0.079*	–0.039	0.046	0.367	–0.113	0.048	0.020**	–0.072	0.052	0.167
Social trust	–0.076	0.052	0.140	–0.068	0.052	0.194	–0.019	0.061	0.758	–0.009	0.061	0.878
0|1	0.553	0.309		0.417	0.320		0.344	0.363		0.202	0.371	
1|2	1.324	0.302		1.190	0.310		0.824	0.365		0.686	0.374	
2|3	2.055	0.346		1.923	0.356		1.357	0.381		1.225	0.389	
Obs.	*2,929*						*2,919*					

Abbreviations: SH, Subjective Happiness.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table B.7: First stage on subjective happiness using social satisfaction and social trust as IVs

Outcome variable: subjective happiness	Crack/cocaine use			Injection drug use		
	β	*SE*	*p*	*β*	*SE*	*p*
Constant	0.947	0.089	0.000***	0.945	0.089	0.000***
Male	–0.022	0.022	0.337	–0.023	0.023	0.311
Age	–0.000	0.001	0.392	–0.000	0.001	0.391
Age^2	–0.000	0.000	0.005***	0.000	0.000	0.005***
White	–0.049	0.041	0.229	–0.044	0.041	0.289
Black	–0.090	0.052	0.085*	–0.088	0.053	0.095*
Hispanic	0.071	0.039	0.067*	0.074	0.039	0.059*
Years of education	–0.003	0.005	0.548	–0.003	0.005	0.556
Current family income	0.060	0.013	0.000***	0.060	0.013	0.000***
Living in a small town at 16yo	0.046	0.033	0.160	0.045	0.033	0.169
Living in a large town at 16yo	0.038	0.038	0.319	0.038	0.038	0.316
Living in suburb at 16yo	–0.015	0.038	0.689	–0.019	0.038	0.610
Living in open country/on a farm at 16yo	0.057	0.039	0.145	0.059	0.039	0.133
Living with both parents at 16yo	0.085	0.055	0.123	0.089	0.056	0.112
Divorced or separated parents at 16yo	0.089	0.061	0.148	0.088	0.062	0.151
One or both parents died at 16yo	0.220	0.076	0.004***	0.223	0.077	0.004***
Family income at 16yo	–0.008	0.013	0.528	–0.009	0.013	0.496
Social satisfaction	0.251	0.011	0.000***	0.251	0.011	0.000***
Social trust	0.045	0.013	0.001***	0.043	0.013	0.001***
F statistic		37.82***			37.59***	
R^2		0.1896			0.1892	

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table B.8: Estimates with IVs without bootstrapped SEs

	Crack/cocaine use (obs. 2,929)						Injection drug use (obs. 2,919)					
	OLS			Ordered Probit			OLS			Ordered Probit		
	β	*SE*	*p*	*β*	*SE*	*p*	*β*	*SE*	*p*	*β*	*SE*	*p*
Constant	0.253	0.060	0.000***				0.229	0.056	0.000***			
Male	0.015	0.010	0.118	0.163	0.086	0.058*	0.000	0.009	0.983	0.026	0.104	0.804
Age	–0.000	0.000	0.151	–0.006	0.003	0.029**	–0.001	0.000	0.005***	–0.006	0.003	0.054*
Age^2	–0.000	0.000	0.001***	–0.001	0.000	0.000***	0.000	0.000	0.190	–0.000	0.000	0.056*
White	0.004	0.016	0.788	0.028	0.168	0.868	–0.001	0.015	0.918	–0.080	0.185	0.665
Black	0.016	0.024	0.491	0.107	0.196	0.587	–0.017	0.023	0.445	–0.348	0.237	0.141
Hispanic	–0.026	0.016	0.099*	–0.248	0.162	0.125	–0.041	0.014	0.002***	–0.450	0.205	0.028**
Years of education	–0.006	0.002	0.000***	–0.071	0.019	0.000***	–0.005	0.002	0.004***	–0.064	0.023	0.005***
Current family income	–0.022	0.007	0.001***	–0.194	0.052	0.000***	–0.014	0.006	0.021**	–0.133	0.062	0.033**
Subjective happiness	–0.046	0.022	0.039**	–0.353	0.155	0.024**	–0.031	0.019	0.096*	–0.459	0.189	0.015**
Living in a small town at 16yo	0.015	0.013	0.244	0.200	0.136	0.142	0.005	0.014	0.712	0.108	0.150	0.472
Living in a large town at 16yo	0.032	0.018	0.082*	0.353	0.148	0.017**	0.014	0.017	0.420	0.205	0.171	0.230
Living in suburb at 16yo	0.034	0.016	0.040**	0.368	0.151	0.015**	0.015	0.016	0.359	0.214	0.169	0.206
Living in open country/on a farm at 16yo	0.018	0.016	0.249	0.182	0.160	0.256	–0.032	0.012	0.010**	–0.560	0.252	0.026**
Living with both parents at 16yo	–0.047	0.031	0.126*	–0.290	0.171	0.090*	–0.033	0.033	0.313	–0.219	0.206	0.286
Divorced or separated parents at 16yo	0.019	0.037	0.609	0.148	0.183	0.417	–0.027	0.035	0.434	–0.095	0.225	0.672
One or both parents died at 16yo	–0.013	0.043	0.756	–0.050	0.250	0.842	0.001	0.046	0.982	0.041	0.296	0.890
Family income at 16yo	0.011	0.005	0.038**	0.109	0.049	0.025**	–0.003	0.005	0.523	–0.002	0.060	0.977
0|1				0.263	0.386					–0.070	0.456	
1|2				1.034	0.390					0.413	0.458	
2|3				1.769	0.421					0.953	0.471	
Residuals$_{HAPPINESS}$				0.199	0.170	0.242				0.286	0.205	
F statistic	*285.23*		*0.000****				*283.786*		*0.000****			
Wu–Hausman	*1.813*		*0.178*				*0.397*		*0.528*			
Sargan–Hansen	*0.760*		*0.383*				*0.123*		*0.726*			
Multiple R^2 or Pseudo R^2		*0.0324*			*0.0992*			*0.0221*			*0.0799*	

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table B.9: First stage estimation on subjective happiness using social satisfaction as IV

	Crack/cocaine use			Injection drug use		
	β	*SE*	*p*	*β*	*SE*	*p*
Constant	0.978	0.088	0.000***	0.974	0.088	0.000***
Male	–0.017	0.022	0.440	–0.019	0.023	0.400
Age	0.000	0.001	0.616	0.000	0.001	0.605
Age^2	0.000	0.000	0.007***	0.000	0.000	0.008***
White	–0.048	0.041	0.245	–0.042	0.041	0.310
Black	–0.105	0.052	0.044**	–0.102	0.052	0.053*
Hispanic	0.060	0.039	0.125	0.062	0.039	0.108
Years of education	0.000	0.005	0.990	0.000	0.005	0.985
Current family income	0.064	0.013	0.000***	0.064	0.013	0.000***
Living in a small town at 16yo	0.044	0.033	0.181	0.043	0.033	0.193
Living in a large town at 16yo	0.039	0.038	0.300	0.040	0.038	0.299
Living in suburb at 16yo	–0.014	0.038	0.707	–0.018	0.038	0.624
Living in open country/on a farm at 16yo	0.052	0.039	0.184	0.054	0.039	0.168
Living with both parents at 16yo	0.088	0.055	0.115	0.091	0.056	0.103
Divorced or separated parents at 16yo	0.087	0.061	0.155	0.087	0.062	0.156
One or both parents died at 16yo	0.224	0.077	0.003***	0.227	0.077	0.003***
Family income at 16yo	–0.007	0.013	0.570	–0.008	0.013	0.536
Social satisfaction	0.255	0.011	0.000***	0.255	0.011	0.000***
F statistic		39.20***			39.03***	

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table B.10: Estimates using social satisfaction as IV with bootstrapped SEs

	Crack/cocaine use (obs. 2,929)						Injection drug use (obs. 2,919)					
	OLS			Ordered Probit			OLS			Ordered Probit		
	β	*SE*	*p*	*β*	*SE*	*p*	*β*	*SE*	*p*	*β*	*SE*	*p*
Constant	0.249	0.061	0.000***				0.230	0.056	0.000***			
Male	0.016	0.010	0.117	0.163	0.087	0.061*	0.000	0.009	0.982	0.026	0.106	0.805
Age	0.000	0.000	0.149	–0.006	0.003	0.049**	–0.001	0.000	0.005***	–0.006	0.003	0.063*
Age^2	0.000	0.000	0.001***	–0.001	0.000	0.000***	0.000	0.000	0.189	–0.000	0.000	0.049**
White	0.004	0.016	0.784	0.029	0.176	0.870	–0.001	0.015	0.917	–0.080	0.229	0.725
Black	0.017	0.024	0.487	0.109	0.200	0.586	–0.017	0.023	0.443	–0.349	0.282	0.215
Hispanic	–0.027	0.016	0.095*	–0.251	0.172	0.143	–0.041	0.014	0.003***	–0.450	0.326	0.167
Years of education	–0.006	0.002	0.000***	–0.071	0.019	0.000***	–0.005	0.002	0.004***	–0.064	0.024	0.007***
Current family income	–0.023	0.007	0.001***	–0.197	0.054	0.000***	–0.014	0.006	0.022**	–0.133	0.066	0.043**
Subjective happiness	–0.043	0.023	0.057*	–0.328	0.179	0.066*	–0.032	0.019	0.093*	–0.459	0.196	0.019**
Living in a small town at 16yo	0.015	0.013	0.248	0.198	0.141	0.160	0.005	0.014	0.710	0.108	0.162	0.505
Living in a large town at 16yo	0.032	0.018	0.082*	0.352	0.154	0.023**	0.014	0.017	0.419	0.205	0.183	0.261
Living in suburb at 16yo	0.034	0.016	0.040**	0.368	0.147	0.012**	0.015	0.016	0.359	0.213	0.183	0.245
Living in open country/on a farm at 16yo	0.018	0.017	0.252	0.180	0.156	0.248	–0.032	0.012	0.010**	–0.560	0.718	0.437
Living with both parents at 16yo	–0.048	0.031	0.124	–0.292	0.165	0.077*	–0.033	0.033	0.314	–0.220	0.222	0.324
Divorced or separated parents at 16yo	0.018	0.037	0.613	0.147	0.176	0.406	–0.027	0.035	0.436	–0.095	0.236	0.687
One or both parents died at 16yo	–0.014	0.043	0.746	–0.055	0.371	0.883	0.001	0.046	0.978	0.041	0.674	0.951
Family income at 16yo	0.011	0.005	0.037**	0.109	0.047	0.019**	–0.003	0.005	0.521	–0.002	0.061	0.978
0|1				0.303	0.438					–0.070	0.485	
1|2				1.074	0.430					0.414	0.484	
2|3				1.809	0.469					0.953	0.501	
Residuals$_{HAPPINESS}$				0.169	0.189	0.371				0.286	0.211	0.176
Weak instruments	554.755		0.000***				552.91		0.000***			
Wu–Hausman	1.385		0.239				0.436		0.509			
Multiple R^2 and McFadden R^2		0.0330			0.0989			0.0220			0.0799	

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table B.11: First stage estimation on subjective happiness using social trust as IV

	Crack/cocaine use			Injection drug use		
	β	*SE*	*p*	*β*	*SE*	*p*
Constant	1.573	0.091	0.000***	1.569	0.092	0.000***
Male	–0.021	0.024	0.399	–0.022	0.024	0.370
Age	0.000	0.001	0.922	0.000	0.001	0.929
Age^2	–0.000	0.000	0.020**	0.000	0.000	0.021**
White	–0.037	0.045	0.406	–0.035	0.045	0.438
Black	–0.050	0.057	0.377	–0.049	0.057	0.386
Hispanic	0.114	0.042	0.007***	0.111	0.042	0.009***
Years of education	–0.003	0.005	0.597	–0.003	0.005	0.568
Current family income	0.111	0.014	0.000***	0.112	0.014	0.000***
Living in a small town at 16yo	0.059	0.035	0.095*	0.058	0.036	0.101*
Living in a large town at 16yo	0.037	0.041	0.372	0.038	0.041	0.359
Living in suburb at 16yo	–0.006	0.041	0.882	–0.010	0.041	0.803
Living in open country/on a farm at 16yo	0.058	0.042	0.173	0.060	0.042	0.156
Living with both parents at 16yo	0.087	0.060	0.146	0.097	0.061	0.110
Divorced or separated parents at 16yo	0.095	0.066	0.153	0.100	0.067	0.134
One or both parents died at 16yo	0.237	0.083	0.004***	0.247	0.083	0.003***
Family income at 16yo	–0.017	0.014	0.231	–0.017	0.014	0.212
Social trust	0.076	0.014	0.000***	0.074	0.014	0.000***
F statistic		8.35***			8.29***	

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table B.12: Estimates using social trust as IV with bootstrapped SEs

	Crack/cocaine use (2,929)						Injection drug use (2,919)					
	OLS			Ordered Probit			OLS			Ordered Probit		
	β	*SE*	*p*	*β*	*SE*	*p*	*β*	*SE*	*p*	*β*	*SE*	*p*
Constant	0.356	0.133	0.004***				0.191	0.120	0.118			
Male	0.015	0.010	0.151	0.153	0.088	0.082*	0.000	0.009	0.986	0.022	0.106	0.832
Age	0.000	0.000	0.193	–0.006	0.003	0.070*	–0.001	0.000	0.005***	–0.006	0.003	0.073*
Age^2	0.000	0.000	0.001***	–0.001	0.000	0.000***	0.000	0.000	0.267	–0.000	0.000	0.060*
White	0.002	0.017	0.893	–0.002	0.176	0.990	–0.001	0.017	0.959	–0.082	0.234	0.726
Black	0.012	0.025	0.634	0.049	0.199	0.806	–0.016	0.022	0.505	–0.351	0.290	0.226
Hispanic	–0.020	0.018	0.263	–0.179	0.192	0.349	–0.043	0.017	0.003**	–0.452	0.335	0.178
Years of education	–0.006	0.002	0.001***	–0.070	0.019	0.000***	–0.005	0.002	0.005***	–0.065	0.024	0.007**
Current family income	–0.015	0.011	0.188	–0.104	0.099	0.291	–0.017	0.010	0.080*	–0.138	0.116	0.235
Subjective happiness	–0.108	0.073	0.141	–1.111	0.695	0.110	–0.008	0.070	0.903	–0.403	0.816	0.622
Living in a small town at 16yo	0.019	0.014	0.179	0.244	0.145	0.093*	0.004	0.014	0.785	0.109	0.165	0.512
Living in a large town at 16yo	0.034	0.019	0.069*	0.386	0.154	0.012**	0.013	0.016	0.456	0.212	0.182	0.246
Living in suburb at 16yo	0.033	0.017	0.047**	0.371	0.146	0.012**	0.015	0.015	0.353	0.221	0.183	0.227
Living in open country/on a farm at 16yo	0.022	0.016	0.183	0.221	0.159	0.164	–0.033	0.016	0.010**	–0.548	0.715	0.443
Living with both parents at 16yo	–0.042	0.032	0.194	–0.233	0.178	0.189	–0.036	0.024	0.282	–0.235	0.225	0.295
Divorced or separated parents at 16yo	0.024	0.038	0.522	0.205	0.189	0.278	–0.030	0.026	0.405	–0.104	0.243	0.668
One or both parents died at 16yo	0.002	0.047	0.968	0.128	0.395	0.746	–0.005	0.036	0.922	0.010	0.693	0.988
Family income at 16yo	0.010	0.006	0.072*	0.097	0.048	0.044**	–0.003	0.005	0.588	0.002	0.061	0.970
0|1				–0.999	0.136					0.020	1.414	
1|2				–0.228	0.152					0.503	1.405	
2|3				0.502	0.222					1.044	1.421	
Residuals$_{HAPPINESS}$				0.934	0.690	0.176				0.186	0.814	0.819
Weak instruments	29.263		0.000***				28.637		0.000***			
Wu–Hausman	1.353		0.245				0.037		0.848			
Multiple R^2 or Pseudo R^2		0.000			0.0996			0.0218			0.0776	

*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table B.13: Marginal effects from the Ordered Probit model for crack/cocaine use

Dependent variable: Crack/cocaine use *(Obs. 2,929)*	**Never used**		**More than 3 years ago**		**More than 12 months ago but within 3 years**		**In the past 30 days**	
	Marg. Eff.	**z stat.**	**Marg. Eff.**	**z stat.**	**Marg. Eff.**	**z stat.**	**Marg. Eff.**	**z stat.**
Male	–.0145024	–1.92	.0109515	1.92	.0029523	1.81	.0005986	1.38
Age	.0005735	2.17	–.0004331	–2.16	–.0001168	–2.01	–.0000237	–1.49
Age^2	.0000652	4.15	–.0000493	–4.13	–.0000133	–3.28	−0.000003	–1.78
White	–.0028719	–0.20	.0021687	0.20	.0005846	0.20	.0001185	0.20
Black	–.0105161	–0.61	.0079412	0.61	.0021408	0.61	.000434	0.59
Hispanic	.0235788	1.67	–.0178056	–1.67	–.0048	–1.60	–.0009732	–1.28
Years of education	.0062437	3.65	–.004715	–3.63	–.0012711	–3.00	–.0002577	–1.75
Current family income	.0186329	4.22	–.0140707	–4.18	–.0037932	–3.32	–.0007691	–1.81
Subjective happiness	.016338	2.85	–.0123376	–2.84	–.003326	–2.50	–.0006743	–1.63
Living in a small town at 16yo	–.0164163	–1.38	.0123968	1.38	.0033419	1.33	.0006776	1.13
Living in a large town at 16yo	–.0303626	–2.34	.0229284	2.34	.006181	2.14	.0012532	1.51
Living in suburb at 16yo	–.0323505	–2.43	.0244295	2.43	.0065857	2.22	.0013352	1.54
Living in open country/on a farm at 16yo	–.0150286	–1.07	.0113489	1.07	.0030594	1.05	.0006203	0.94
Living with both parents at 16yo	.0270823	1.82	–.0204512	–1.81	–.0055133	–1.73	–.0011178	–1.34
Divorced or separated parents at 16yo	–.0113683	–0.71	.0085848	0.71	.0023143	0.71	.0004692	0.67
One or both parents died at 16yo	.0077519	0.36	–.0058539	–0.36	–.0015781	–0.36	–.00032	–0.35
Family income at 16yo	–.00974	–2.28	.0073552	2.27	.0019828	2.10	.000402	1.50

Table B.14: Marginal effects from the Ordered Probit model for injection drug use

Dependent variable: Injection drug use *(Obs. 2,919)*								
	Never used		**More than 3 years ago**		**More than 12 months ago but within 3 years**		**In the past 30 days**	
	Marg. Eff.	**z stat.**	**Marg. Eff.**	**z stat.**	**Marg. Eff.**	**z stat.**	**Marg. Eff.**	**z stat.**
Male	–.0014429	–0.25	.0008959	0.25	.0004017	0.25	.0001453	0.25
Age	.0003636	1.88	–.0002258	–1.85	–.0001012	–1.76	–.0000366	–1.57
Age^2	.00002	1.80	–.0000124	–1.79	−0.000006	–1.70	−0.000002	–1.48
White	.0043046	0.42	–.0026727	–0.42	–.0011983	–0.42	–.0004336	–0.41
Black	.0190417	1.43	–.0118231	–1.42	–.0053007	–1.38	–.0019179	–1.24
Hispanic	.0264012	2.27	–.0163927	–2.24	–.0073494	–2.08	–.0026591	–1.73
Years of education	.003656	2.75	–.00227	–2.69	–.0010177	–2.42	–.0003682	–1.92
Current family income	.0089762	2.63	–.0055734	–2.58	–.0024987	–2.33	–.0009041	–1.87
Subjective happiness	.0122615	2.70	–.0076133	–2.65	–.0034133	–2.38	–.001235	–1.90
Living in a small town at 16yo	–.005539	–0.66	.0034392	0.66	.0015419	0.65	.0005579	0.64
Living in a large town at 16yo	–.0114745	–1.19	.0071246	1.19	.0031942	1.16	.0011557	1.08
Living in suburb at 16yo	–.0125141	–1.31	.0077701	1.31	.0034836	1.27	.0012604	1.17
Living in open country/on a farm at 16yo	.0313258	2.19	–.0194504	–2.16	–.0087203	–2.01	–.0031551	–1.70
Living with both parents at 16yo	.0143084	1.25	–.0088842	–1.24	–.0039831	–1.22	–.0014411	–1.12
Divorced or separated parents at 16yo	.0068642	0.55	–.004262	–0.55	–.0019108	–0.54	–.0006914	–0.54
One or both parents died at 16yo	.0020539	0.13	–.0012753	–0.13	–.0005718	–0.13	–.0002069	–0.13
Family income at 16yo	–.0003011	–0.09	.000187	0.09	.0000838	0.09	.0000303	0.09

Table B.15: Marginal effects from the Ordered Probit model with IVs for crack/cocaine use

Dependent variable: Crack/cocaine use *(Obs. 2,929)*								
	Never used		**More than 3 years ago**		**More than 12 months ago but within 3 years**		**In the past 30 days**	
	Marg. Eff.	*z stat.*	*Marg. Eff.*	*z stat.*	*Marg. Eff.*	*z stat.*	*Marg. Eff.*	*z stat.*
Male	–.0142689	–1.86	.0107769	1.83	.0029075	1.83	.0005845	1.44
Age	.0005723	1.94	–.0004323	–1.97	–.0001166	–1.74	–.0000234	–1.37
Age^2	.0000664	3.72	–.0000502	–3.48	–.0000135	–3.47	−.000000	–1.95
White	–.002439	–0.16	.0018421	0.16	.000497	0.16	.0000999	0.16
Black	–.0093445	–0.53	.0070576	0.53	.0019041	0.53	.0003828	0.50
Hispanic	.0216854	1.44	–.0163784	–1.44	–.0044187	–1.36	–.0008883	–1.31
Years of education	.0061983	3.61	–.0046814	–3.55	–.001263	–3.04	–.0002539	–1.80
Current family income	.0169837	3.47	–.0128273	–3.47	–.0034607	–2.85	–.0006957	–1.76
Subjective happiness	.0308401	1.99	–.0232927	–1.99	–.0062841	–1.89	–.0012634	–1.38
Living in a small town at 16yo	–.0175194	–1.41	.0132319	1.40	.0035698	1.35	.0007177	1.23
Living in a large town at 16yo	–.0308649	–2.26	.0233114	2.25	.0062892	2.08	.0012644	1.52
Living in suburb at 16yo	–.0321911	–2.45	.024313	2.44	.0065594	2.17	.0013187	1.70
Living in open country/on a farm at 16yo	–.0159408	–1.16	.0120396	1.16	.0032482	1.15	.000653	1.01
Living with both parents at 16yo	.0253373	1.75	–.0191365	–1.73	–.0051628	–1.70	–.0010379	–1.42
Divorced or separated parents at 16yo	–.0129651	–0.84	.0097922	0.84	.0026418	0.82	.0005311	0.74
One or both parents died at 16yo	.0043755	0.14	–.0033047	–0.14	–.0008916	–0.14	–.0001792	–0.14
Family income at 16yo	–.0095616	–2.28	.0072216	2.29	.0019483	2.00	.0003917	1.63

Table B.16: Marginal effects from the Ordered Probit model with IVs for injection drug use

Dependent variable: Injection drug use *(Obs. 2,919)*								
	Never used		**More than 3 years ago**		**More than 12 months ago but within 3 years**		**In the past 30 days**	
	Marg. Eff.	*z stat.*	*Marg. Eff.*	*z stat.*	*Marg. Eff.*	*z stat.*	*Marg. Eff.*	*z stat.*
Male	–.0014481	–0.24	.0008971	0.24	.0004031	0.24	.000148	0.24
Age	.0003667	1.79	–.0002271	–1.93	–.0001021	–1.54	–.0000375	–1.30
Age^2	.000021	1.95	–.000013	–1.91	–.00000585	–1.89	–.00000215	–1.46
White	.0044874	0.35	–.0027798	–0.35	–.0012492	–0.35	–.0004585	–0.34
Black	.0195143	1.19	–.0120883	–1.17	–.0054323	–1.16	–.0019937	–1.14
Hispanic	.0251741	1.43	–.0155944	–1.41	–.0070078	–1.41	–.002572	–1.22
Years of education	.0036004	2.51	–.0022303	–2.58	–.0010023	–2.09	–.0003678	–1.70
Current family income	.0074648	1.95	–.0046241	–1.99	–.002078	–1.75	–.0007627	–1.44
Subjective happiness	.0256834	2.23	–.0159098	–2.15	–.0071496	–2.15	–.002624	–1.58
Living in a small town at 16yo	–.0060293	–0.67	.0037349	0.66	.0016784	0.66	.000616	0.66
Living in a large town at 16yo	–.0114989	–1.12	.0071231	1.11	.003201	1.08	.0011748	1.04
Living in suburb at 16yo	–.0119692	–1.16	.0074144	1.14	.0033319	1.14	.0012229	1.07
Living in open country/on a farm at 16yo	.0313438	0.82	–.0194162	–0.82	–.0087253	–0.79	–.0032023	–0.76
Living with both parents at 16yo	.0122819	0.98	–.0076081	–0.97	–.003419	–0.95	–.0012548	–1.00
Divorced or separated parents at 16yo	.0053379	0.40	–.0033066	–0.40	–.0014859	–0.40	–.0005454	–0.41
One or both parents died at 16yo	–.0023007	–0.06	.0014252	0.06	.0006405	0.06	.0002351	0.06
Family income at 16yo	.0000953	0.03	–.000059	–0.03	–.0000265	–0.03	–.00000973	–0.03

Appendix C

Chapter 3 Appendix

Table C.1: Country-level means of trust in institutions and key indicators, 2008–2023

	T-1	T-2	T-3	T-4	T-5	T-6	T-7	DI	CPI	GDP	UR	GFL	SFL	N. obs.
Argentina	3.971	3.953	3.571	3.797	2.818	3.433	3.330	6.827	33.796	9774.997	64913	.007613	.008703	10,516
Bolivia	4.162	3.927	3.767	3.844	2.927	3.382	3.845	5.743	29.956	1951.521	60356.91	.0045178	.0047665	17,195
Brazil	5.008	3.617	3.272	3.589	2.625	4.068	4.034	7.116	37.792	8839.950	85252.23	.0052321	.0051401	11,535
Chile	4.796	4.541	3.483	4.333	2.842	4.718	4.004	7.873	68.480	13532.87	75833.6	.0047407	.0053278	11,550
Colombia	4.690	3.545	3.593	3.755	2.861	4.052	4.109	7.117	36.593	5442.371	70808.82	.0032672	.0035264	15,253
Dominican Republic	4.491	3.816	3.760	3.899	2.900	3.234	4.439	6.411	29.732	4553.403	67113.03	.0056029	.0064085	10,669
Ecuador	4.957	3.940	3.331	3.946	2.728	3.966	4.152	5.769	27.750	5026.875	55458.11	.0026296	.0028484	13,671
El Salvador	4.913	4.132	3.833	4.512	3.075	4.253	4.039	6.252	35.452	2677.011	58978.06	.0032379	.0041887	10,725
Guatemala	4.693	3.640	3.337	3.986	2.767	3.335	3.416	5.714	28.112	2621.344	49687.73	.0105818	.0124681	10,755
Guyana	4.596	3.886	4.128	3.871	3.787	3.631	4.156	6.100	26.004	4449.382	15434.18	.0003665	.0003654	7,140
Honduras	4.413	3.379	3.527	4.134	3.018	3.614	3.589	5.827	26.269	2186.327	45719.35	.0087579	.0108975	11,129
Jamaica	4.716	3.520	3.335	3.417	3.090	3.375	3.859	7.230	37.308	4442.107	39303.89	.002498	.0026313	10,555
Mexico	5.073	3.820	4.079	4.165	3.054	3.257	4.150	6.449	31.556	10150.23	44987.65	.0037915	.0053104	10,982
Nicaragua	4.682	3.854	3.701	3.974	3.067	4.136	3.903	4.551	24.172	1493.952	50617.49	.0085837	.0105781	12,423
Paraguay	4.307	3.516	3.127	4.071	2.712	3.290	3.415	6.233	25.494	5454.820	60423.15	.0125928	.0129367	10,248
Peru	4.369	3.810	2.714	3.367	2.519	3.440	3.239	6.413	35.644	5889.955	77162.61	.002429	.0024673	11,703
Uruguay	4.351	5.411	4.255	4.176	3.484	4.314	4.354	8.264	70.293	6985.198	94807.04	.0116724	.0143346	10,636
Venezuela	4.001	4.179	3.743	4.165	3.237	3.067	3.622	5.115	18.985	10496.97	88094.35	.0021142	.0020184	7,558

Note: Trust variables are survey-weighted means using LAPOP's post-stratification weights. T-1, Trust in army; T-2, Trust in elections; T-3, Trust in congress; T-4, Trust in municipality; T-5, Trust in political parties; T-6, Trust in police; T-7, Trust in president; DI, Democracy index; CPI, Corruption perception index; GDP, Gross domestic product per capita; UR, Urbanization rate; GFL, General forest cover loss; SFL, Specific forest cover loss.

Table C.2: Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	Trust in army	1.0000												
(2)	Trust in elections	0.3289	1.0000											
(3)	Trust in congress	0.4252	0.4885	1.0000										
(4)	Trust in municipality	0.3043	0.4081	0.4122	1.0000									
(5)	Trust in political parties	0.2771	0.4787	0.5239	0.3991	1.0000								
(6)	Trust in police	0.4618	0.4045	0.4595	0.3914	0.3931	1.0000							
(7)	Trust in president	0.3441	0.4998	0.4762	0.3935	0.4625	0.3901	1.0000						
(8)	Democracy index	0.0383	0.0913	0.0072	–0.0087	0.0064	0.1076	0.0363	1.0000					
(9)	Corruption perception index	0.0289	0.1615	0.0359	0.0281	0.0236	0.1640	0.0353	0.7593	1.0000				
(10)	GDP per capita	0.0070	0.0519	–0.0090	–0.0103	–0.0120	0.0421	–0.0037	0.3435	0.3899	1.0000			
(11)	Urbanization rate	–0.0358	0.0531	–0.0322	–0.0123	–0.0460	0.0379	–0.0091	0.2639	0.2805	0.2146	1.0000		
(12)	General tree cover loss	–0.0348	0.0189	0.0026	0.0430	–0.0150	0.0011	–0.0400	0.0148	0.0988	–0.1059	0.0132	1.0000	
(13)	Specific tree cover loss	–0.0289	0.0320	0.0202	0.0514	–0.0004	0.0070	–0.0257	0.0053	0.1085	–0.0885	–0.0166	0.9835	1.0000

Table C.3: Exploratory Factor Analysis (EFA)

Variables	Factor	Uniqueness	Scoring coefficients
Trust in president	0.7258	0.4732	0.20705
Trust in congress	0.7752	0.3990	0.22116
Trust in political parties	0.7210	0.4801	0.20569
Trust in elections	0.7363	0.4579	0.21005
Trust in municipality	0.6615	0.5625	0.18871
Trust in police	0.7045	0.5037	0.20097
Trust in army	0.6179	0.6182	0.17627

Figure C.1: Parallel analysis scree plots

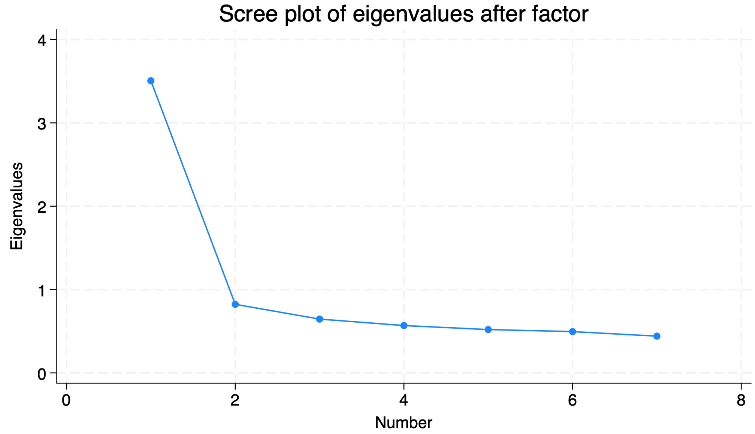


Table C.4: VIF test

Variables	VIF General Model	VIF Specific Model
Tree cover loss	3.85	3.78
GDP per capita	3.55	3.71
Democracy index	6.47	6.48
Corruption perception index	27.76	27.76
Urbanization rate	1.84	1.85
Countries		
Bolivia	4.19	4.16
Brazil	2.29	2.31
Chile	11.96	11.97
Colombia	3.29	3.23
Dominican Republic	2.39	2.37
Ecuador	3.49	3.44
El Salvador	3.01	2.93
Guatemala	3.19	3.24
Guyana	2.67	2.63
Honduras	3.35	3.42
Jamaica	2.50	2.44
Mexico	2.30	2.22
Nicaragua	4.41	4.46
Paraguay	2.88	2.76
Peru	2.67	2.63
Uruguay	12.01	12.16
Venezuela	3.43	3.47
Years		
2009	1.24	1.23
2010	1.80	1.80
2011	1.22	1.22
2012	1.91	1.92
2013	1.25	1.25
2014	2.26	2.30
2017	2.06	1.99
2018	1.22	1.22
2019	1.91	1.96
2023	2.17	2.24

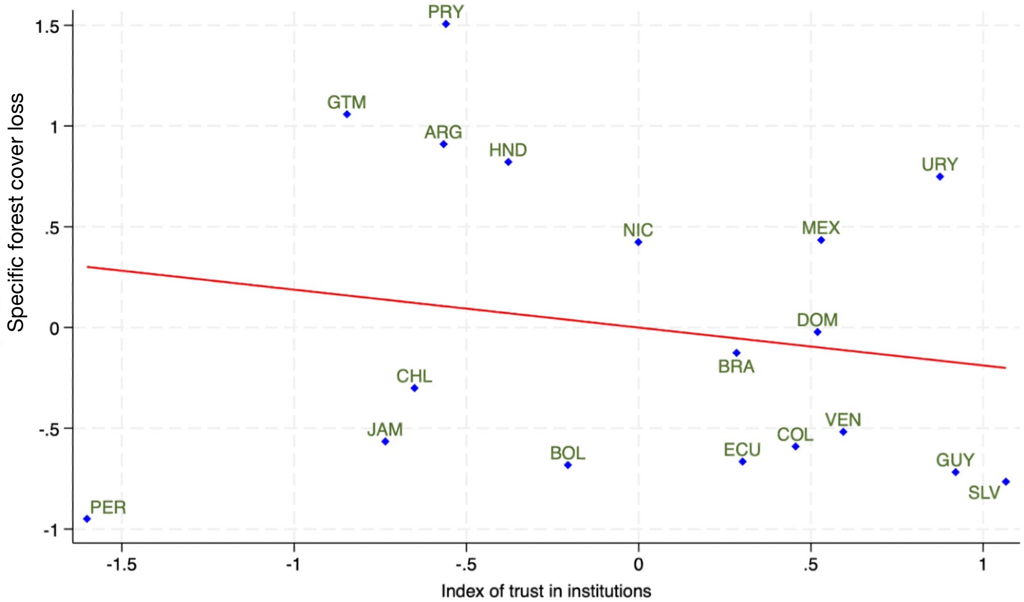
Table C.5: OLS regressions for trust in institutions and general tree cover loss

DV: Trust in institutions	*β*	*SE*	*p*	*95% CI*	
GDP per capita	0.0827	0.3099	0.794	–0.5867	0.7522
Democracy index	–0.6953	0.4452	0.142	–1.6570	0.2664
Corruption perception index	1.1758	0.3979	0.011**	0.3162	2.0353
Urbanization rate	–0.4413	0.3514	0.231	–1.2006	0.3179
Constant	0.0068	0.1979	0.973	–0.4208	0.4344
F statistic			2.83*		
Adjusted R^2			0.3007		

DV: General tree cover loss	*β*	*SE*	*p*	*95% CI*	
GDP per capita	–0.3922	0.3319	0.258	–1.1092	0.3247
Democracy index	–0.1300	0.4768	0.789	–1.1570	0.9000
Corruption perception index	0.2729	0.4261	0.533	–0.6477	1.1935
Urbanization rate	0.3365	0.3764	0.388	–0.4767	1.1497
Constant	0.0269	0.2120	0.901	–0.4311	0.4849
F statistic			0.64		
Adjusted R^2			–0.0936		

DV: Specific tree cover loss	*β*	*SE*	*p*	*95% CI*	
GDP per capita	–0.3907	0.3213	0.246	–1.0849	0.3035
Democracy index	–0.2283	0.4617	0.629	–1.2257	0.7690
Corruption perception index	0.3906	0.4126	0.361	–0.5008	1.2820
Urbanization rate	0.2558	0.3645	0.495	–0.5316	1.0432
Constant	0.0284	0.2053	0.892	–0.4151	0.4719
F statistic			0.58		
Adjusted R^2			–0.0645		

Figure C.2: Relationship between specific forest cover loss and institutional trust in LAC, 2008–2023



Note: Residuals were obtained from two separate OLS regressions: (i) institutional trust on GDP per capita, democracy index, perceived corruption index, and urbanization rate; and (ii) specific tree cover loss on the same set of covariates. Country labels are abbreviated using the ISO 3166-1 alpha-3 standard. Each country is represented by a 3-letter code (ARG = Argentina, BOL = Bolivia, BRA = Brazil, CHL = Chile, COL = Colombia, DOM = Dominican Republic, ECU = Ecuador, SLV = El Salvador, GTM = Guatemala, GUY = Guyana, HND = Honduras, JAM = Jamaica, MEX = Mexico, NIC = Nicaragua, PRY = Paraguay, PER = Peru, URY = Uruguay, VEN = Venezuela).

Table C.6: Impact of general tree cover loss on trust in the army in LAC, 2008–2023

	β	*SE*	*p*	*95% CI*	
General tree cover loss	–0.0306	0.0053	0.000***	–0.0410	–0.0201
GDP per capita	–0.0075	0.0049	0.128	–0.0172	0.0022
Democracy index	0.0264	0.0079	0.001***	0.0108	0.0419
Corruption perception index	0.0921	0.0146	0.000***	0.0634	0.1208
Urbanization rate	–0.0315	0.0038	0.000***	–0.0390	–0.0239
Countries					
Bolivia	0.0789	0.0312	0.011**	0.0178	0.1400
Brazil	0.4039	0.0210	0.000***	0.3628	0.4451
Chile	0.0785	0.0394	0.046**	0.0013	0.1557
Colombia	0.2188	0.0208	0.000***	0.1781	0.2596
Dominican Republic	0.2416	0.0214	0.000***	0.1996	0.2836
Ecuador	0.4277	0.0232	0.000***	0.3822	0.4732
El Salvador	0.3625	0.0251	0.000***	0.3133	0.4117
Guatemala	0.3656	0.0273	0.000***	0.3121	0.4192
Guyana	0.2397	0.0288	0.000***	0.1832	0.2962
Honduras	0.2378	0.0261	0.000***	0.1867	0.2889
Jamaica	0.2108	0.0219	0.000***	0.1679	0.2537
Mexico	0.4406	0.0208	0.000***	0.3999	0.4813
Nicaragua	0.3901	0.0309	0.000***	0.3295	0.4507
Paraguay	0.2338	0.0244	0.000***	0.1859	0.2816
Peru	0.1214	0.0205	0.000***	0.0811	0.1616
Uruguay	–0.0597	0.0445	0.180	–0.1469	0.0275
Venezuela	0.1361	0.0338	0.000***	0.0699	0.2023
Years					
2009	0.2493	0.0310	0.000***	0.1885	0.3102
2010	0.0967	0.0111	0.000***	0.0749	0.1186
2011	0.1857	0.0302	0.000***	0.1264	0.2450
2012	0.0768	0.0171	0.000***	0.0432	0.1104
2013	1.1927	0.3018	0.000***	0.6011	1.7844
2014	0.0492	0.0127	0.000***	0.0242	0.0741
2017	0.1480	0.0120	0.000***	0.1245	0.1715
2018	–0.0599	0.0324	0.065*	–0.1235	0.0037
2019	0.0253	0.0120	0.036**	0.0017	0.0490
2023	–0.0115	0.0125	0.356	–0.0359	0.0129
Constant	–0.3021	0.0195	0.000***	–0.3404	–0.2637
F statistic			72.68***		
R^2			0.0116		
N. Obs.			197,406		

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table C.7: Impact of general tree cover loss on trust in elections in LAC, 2008–2023

	β	*SE*	*p*	*95% CI*	
General tree cover loss	–0.0283	0.0057	0.000***	–0.0396	–0.0170
GDP per capita	–0.0015	0.0047	0.747	–0.0108	0.0078
Democracy index	–0.0465	0.0077	0.000***	–0.0616	–0.0313
Corruption perception index	0.0939	0.0151	0.000***	0.0643	0.1235
Urbanization rate	–0.0240	0.0038	0.000***	–0.0315	–0.0165
Countries					
Bolivia	–0.1200	0.0280	0.000***	–0.1748	–0.0652
Brazil	–0.1683	0.0206	0.000***	–0.2087	–0.1280
Chile	0.0461	0.0401	0.250	–0.0324	0.1247
Colombia	–0.2237	0.0191	0.000***	–0.2613	–0.1862
Dominican Republic	–0.0627	0.0197	0.001***	–0.1014	–0.0241
Ecuador	–0.0764	0.0212	0.000***	–0.1180	–0.0347
El Salvador	0.0029	0.0224	0.897	–0.0410	0.0468
Guatemala	–0.1412	0.0233	0.000***	–0.1869	–0.0955
Guyana	–0.1721	0.0336	0.000***	–0.2380	–0.1062
Honduras	–0.2510	0.0253	0.000***	–0.3007	–0.2013
Jamaica	–0.2571	0.0193	0.000***	–0.2950	–0.2191
Mexico	–0.0980	0.0203	0.000***	–0.1378	–0.0581
Nicaragua	–0.0874	0.0285	0.002***	–0.1433	–0.0316
Paraguay	–0.1314	0.0232	0.000***	–0.1769	–0.0859
Peru	–0.1195	0.0183	0.000***	–0.1554	–0.0835
Uruguay	0.4930	0.0435	0.000***	0.4078	0.5782
Venezuela	0.0756	0.0326	0.021**	0.0116	0.1396
Years					
2009	0.1117	0.0303	0.000***	0.0523	0.1711
2010	0.0738	0.0129	0.000***	0.0486	0.0990
2011	0.0560	0.0320	0.080*	–0.0067	0.1188
2012	0.0146	0.0166	0.380	–0.0180	0.0472
2013	0.8219	0.2233	0.000***	0.3841	1.2597
2014	–0.0986	0.0131	0.000***	–0.1243	–0.0729
2017	–0.0932	0.0121	0.000***	–0.1170	–0.0695
2018	–0.1924	0.0326	0.000***	–0.2563	–0.1285
2019	–0.1416	0.0122	0.000***	–0.1656	–0.1176
2023	–0.1928	0.0125	0.000***	–0.2172	–0.1683
Constant	0.1180	0.0170	0.000***	0.0847	0.1514
F statistic			199.04***		
R^2			0.0086		
N. Obs.			197,925		

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table C.8: Impact of general tree cover loss on trust in congress in LAC, 2008–2023

	β	*SE*	*p*	*95% CI*	
General tree cover loss	–0.0260	0.0047	0.000***	–0.0353	–0.0168
GDP per capita	–0.0085	0.0040	0.032**	–0.0162	–0.0007
Democracy index	–0.0690	0.0066	0.000***	–0.0820	–0.0560
Corruption perception index	0.1574	0.0142	0.000***	0.1295	0.1854
Urbanization rate	–0.0218	0.0033	0.000***	–0.0282	–0.0154
Countries					
Bolivia	–0.0329	0.0227	0.147	–0.0774	0.0116
Brazil	–0.1564	0.0159	0.000***	–0.1875	–0.1252
Chile	–0.3790	0.0373	0.000***	–0.4522	–0.3058
Colombia	–0.0483	0.0158	0.002***	–0.0792	–0.0174
Dominican Republic	0.0723	0.0153	0.000***	0.0423	0.1022
Ecuador	–0.1539	0.0180	0.000***	–0.1891	–0.1187
El Salvador	–0.0074	0.0216	0.732	–0.0498	0.0350
Guatemala	–0.1088	0.0195	0.000***	–0.1471	–0.0704
Guyana	0.1330	0.0250	0.000***	0.0839	0.1820
Honduras	–0.0219	0.0204	0.283	–0.0619	0.0181
Jamaica	–0.1759	0.0172	0.000***	–0.2095	–0.1422
Mexico	0.1485	0.0151	0.000***	0.1190	0.1781
Nicaragua	–0.0101	0.0232	0.665	–0.0556	0.0355
Paraguay	–0.0996	0.0185	0.000***	–0.1359	–0.0633
Peru	–0.4111	0.0149	0.000***	–0.4403	–0.3819
Uruguay	–0.0388	0.0403	0.335	–0.1178	0.0401
Venezuela	0.0769	0.0255	0.003***	0.0270	0.1268
Years					
2009	0.1142	0.0327	0.000***	0.0502	0.1783
2010	0.1243	0.0102	0.000***	0.1044	0.1442
2011	0.1733	0.0262	0.000***	0.1219	0.2247
2012	0.0749	0.0140	0.000***	0.0474	0.1025
2013	1.7621	0.3567	0.000***	1.0628	2.4615
2014	–0.0308	0.0109	0.005***	–0.0522	–0.0094
2017	0.0371	0.0107	0.001***	0.0161	0.0580
2018	–0.0745	0.0275	0.007***	–0.1283	–0.0206
2019	–0.0437	0.0106	0.000***	–0.0645	–0.0230
2023	–0.0950	0.0105	0.000***	–0.1156	–0.0745
Constant	0.0418	0.0132	0.002***	0.0159	0.0677
F statistic			139.12***		
R^2			0.0121		
N. Obs.			194,479		

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table C.9: Impact of general tree cover loss on trust in municipality in LAC, 2008–2023

	β	*SE*	*p*	*95% CI*	
General tree cover loss	0.0108	0.0062	0.082*	–0.0014	0.0231
GDP per capita	–0.0338	0.0054	0.000***	–0.0445	–0.0232
Democracy index	–0.0437	0.0083	0.000***	–0.0599	–0.0274
Corruption perception index	0.0602	0.0165	0.000***	0.0279	0.0925
Urbanization rate	–0.0130	0.0042	0.002***	–0.0212	–0.0047
Countries					
Bolivia	–0.0999	0.0343	0.004***	–0.1672	–0.0326
Brazil	–0.0934	0.0233	0.000***	–0.1391	–0.0476
Chile	0.1626	0.0451	0.000***	0.0742	0.2511
Colombia	–0.0271	0.0236	0.251	–0.0733	0.0192
Dominican Republic	0.0117	0.0241	0.626	–0.0355	0.0591
Ecuador	–0.0024	0.0248	0.923	–0.0510	0.0462
El Salvador	0.2171	0.0264	0.000***	0.1652	0.2689
Guatemala	–0.0053	0.0267	0.844	–0.0576	0.0471
Guyana	–0.0522	0.0305	0.087*	–0.1120	0.0075
Honduras	0.0630	0.0288	0.029**	0.0064	0.1195
Jamaica	–0.2158	0.0221	0.000***	–0.2591	–0.1724
Mexico	0.1649	0.0217	0.000***	0.1223	0.2075
Nicaragua	–0.0501	0.0323	0.122	–0.1135	0.0134
Paraguay	0.0777	0.0269	0.004***	0.0249	0.1306
Peru	–0.2328	0.0223	0.000***	–0.2766	–0.1890
Uruguay	0.0457	0.0473	0.334	–0.0470	0.1385
Venezuela	0.1651	0.0322	0.000***	0.1020	0.2283
Years					
2009	0.0437	0.0412	0.288	–0.0370	0.1245
2010	0.0211	0.0126	0.093*	–0.0035	0.0457
2011	–0.1021	0.0358	0.004***	–0.1722	–0.0320
2012	0.0070	0.0198	0.724	–0.0319	0.0459
2013	0.8944	0.2325	0.000***	0.4387	1.3501
2014	–0.0725	0.0138	0.000***	–0.0996	–0.0454
2017	–0.0533	0.0128	0.000***	–0.0785	–0.0282
2018	–0.0150	0.0359	0.675	–0.0855	0.0554
2019	–0.0810	0.0129	0.000***	–0.1063	–0.0556
2023	–0.1228	0.0134	0.000***	–0.1492	–0.0964
Constant	0.0280	0.0195	0.150	–0.0101	0.0662
F statistic			68.10***		
R^2			0.0047		
N. Obs.			198,596		

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table C.10: Impact of general tree cover loss on trust in political parties in LAC, 2008–2023

	β	*SE*	*p*	*95% CI*	
General tree cover loss	–0.0230	0.0051	0.000***	–0.0331	–0.0129
GDP per capita	–0.0054	0.0047	0.247	–0.0147	0.0038
Democracy index	–0.0638	0.0076	0.000***	–0.0787	–0.0488
Corruption perception index	0.1907	0.0148	0.000***	0.1616	0.2198
Urbanization rate	–0.0145	0.0036	0.000***	–0.0216	–0.0074
Countries					
Bolivia	–0.0839	0.0303	0.006***	–0.1434	–0.0244
Brazil	–0.1367	0.0180	0.000***	–0.1719	–0.1015
Chile	–0.4308	0.0378	0.000***	–0.5048	–0.3567
Colombia	–0.0398	0.0186	0.032**	–0.0762	–0.0034
Dominican Republic	0.0534	0.0175	0.002***	0.0191	0.0876
Ecuador	–0.0787	0.0190	0.000***	–0.1160	–0.0414
El Salvador	0.0187	0.0205	0.361	–0.0214	0.0588
Guatemala	–0.0128	0.0202	0.528	–0.0524	0.0269
Guyana	0.3664	0.0284	0.000***	0.3107	0.4222
Honduras	0.1216	0.0223	0.000***	0.0778	0.1654
Jamaica	0.0440	0.0178	0.014**	0.0090	0.0789
Mexico	0.0884	0.0176	0.000***	0.0538	0.1230
Nicaragua	0.0894	0.0267	0.001***	0.0370	0.1418
Paraguay	0.0472	0.0205	0.021**	0.0071	0.0874
Peru	–0.2062	0.0161	0.000***	–0.2377	–0.1746
Uruguay	–0.1085	0.0416	0.009***	–0.1901	–0.0270
Venezuela	0.2402	0.0282	0.000***	0.1849	0.2954
Years					
2009	0.0691	0.0379	0.068*	–0.0051	0.1434
2010	0.0602	0.0113	0.000***	0.0381	0.0823
2011	0.0596	0.0336	0.076*	–0.0062	0.1255
2012	0.0714	0.0184	0.000***	0.0352	0.1075
2013	0.9605	0.3161	0.002***	0.3408	1.5803
2014	–0.1119	0.0115	0.000***	–0.1344	–0.0894
2017	–0.1194	0.0109	0.000***	–0.1409	–0.0979
2018	–0.1525	0.0263	0.000***	–0.2041	–0.1009
2019	–0.1353	0.0111	0.000***	–0.1570	–0.1136
2023	–0.1529	0.0117	0.000***	–0.1758	–0.1300
Constant	0.0563	0.0148	0.000***	0.0273	0.0853
F statistic			93.95***		
R^2			0.0052		
N. Obs.			198,108		

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table C.11: Impact of general tree cover loss on trust in police in LAC, 2008–2023

	β	*SE*	*p*	*95% CI*	
General tree cover loss	0.0001	0.0062	0.981	–0.0120	0.0123
GDP per capita	0.0018	0.0053	0.740	–0.0087	0.0122
Democracy index	0.0188	0.0084	0.026**	0.0023	0.0354
Corruption perception index	0.1302	0.0164	0.000***	0.0981	0.1624
Urbanization rate	–0.0083	0.0041	0.044**	–0.0164	–0.0002
Countries					
Bolivia	0.0053	0.0327	0.872	–0.0588	0.0693
Brazil	0.2454	0.0226	0.000***	0.2012	0.2897
Chile	0.2190	0.0435	0.000***	0.1337	0.3042
Colombia	0.2433	0.0221	0.000***	0.2000	0.2865
Dominican Republic	–0.0301	0.0224	0.179	–0.0741	0.0138
Ecuador	0.3119	0.0241	0.000***	0.2647	0.3591
El Salvador	0.3720	0.0279	0.000***	0.3172	0.4267
Guatemala	0.0312	0.0273	0.253	–0.0223	0.0848
Guyana	0.1451	0.0329	0.000***	0.0806	0.2097
Honduras	0.1754	0.0285	0.000***	0.1195	0.2313
Jamaica	–0.0699	0.0225	0.002***	–0.1139	–0.0259
Mexico	–0.0509	0.0214	0.017**	–0.0929	–0.0089
Nicaragua	0.4405	0.0302	0.000***	0.3814	0.4997
Paraguay	0.0286	0.0261	0.273	–0.0226	0.0798
Peru	–0.0073	0.0212	0.731	–0.0489	0.0343
Uruguay	0.0155	0.0484	0.749	–0.0793	0.1103
Venezuela	0.0147	0.0340	0.665	–0.0519	0.0813
Years					
2009	0.0913	0.0395	0.021**	0.0140	0.1687
2010	0.0294	0.0123	0.017**	0.0053	0.0536
2011	0.1433	0.0393	0.000***	0.0662	0.2204
2012	0.0420	0.0185	0.024**	0.0056	0.0783
2013	0.7397	0.2669	0.006***	0.2164	1.2629
2014	–0.0145	0.0134	0.282	–0.0408	0.0119
2017	0.0042	0.0127	0.739	–0.0207	0.0292
2018	–0.0808	0.0349	0.021**	–0.1493	–0.0123
2019	–0.0078	0.0130	0.550	–0.0333	0.0178
2023	–0.0285	0.0133	0.032**	–0.0546	–0.0025
Constant	–0.1369	0.0199	0.000***	–0.1759	–0.0978
F statistic			147.65***		
R^2			0.0120		
N. Obs.			200,532		

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table C.12: Impact of general tree cover loss on trust in president in LAC, 2008–2023

	β	*SE*	*p*	*95% CI*	
General tree cover loss	–0.0070	0.0069	0.310	–0.0206	0.0065
GDP per capita	–0.0142	0.0061	0.020**	–0.0262	–0.0022
Democracy index	–0.0914	0.0100	0.000***	–0.1111	–0.0718
Corruption perception index	–0.0213	0.0200	0.287	–0.0604	0.0179
Urbanization rate	–0.0316	0.0049	0.000***	–0.0412	–0.0219
Countries					
Bolivia	0.0134	0.0336	0.689	–0.0523	0.0793
Brazil	0.3363	0.0250	0.000***	0.2873	0.3853
Chile	0.4514	0.0506	0.000***	0.3522	0.5507
Colombia	0.3218	0.0256	0.000***	0.2716	0.3719
Dominican Republic	0.4115	0.0263	0.000***	0.3598	0.4631
Ecuador	0.1744	0.0256	0.000***	0.1242	0.2247
El Salvador	0.2583	0.0327	0.000***	0.1942	0.3225
Guatemala	–0.1042	0.0269	0.000***	–0.1570	–0.0515
Guyana	0.0834	0.0396	0.035**	0.0058	0.1610
Honduras	–0.0467	0.0286	0.103	–0.1028	0.0095
Jamaica	0.2059	0.0252	0.000***	0.1565	0.2553
Mexico	0.2834	0.0243	0.000***	0.2357	0.3311
Nicaragua	–0.0279	0.0393	0.477	–0.1050	0.0491
Paraguay	–0.0455	0.0287	0.113	–0.1018	0.0107
Peru	–0.0795	0.0223	0.000***	–0.1232	–0.0358
Uruguay	0.6499	0.0542	0.000***	0.5437	0.7562
Venezuela	–0.0951	0.0374	0.011**	–0.1685	–0.0217
Years					
2009	0.2981	0.0427	0.000***	0.2144	0.3818
2010	0.1047	0.0156	0.000***	0.0741	0.1354
2011	0.1549	0.0387	0.000***	0.0790	0.2309
2012	–0.0066	0.0212	0.757	–0.0482	0.0351
2013	0.2542	0.1714	0.138	–0.0818	0.5903
2014	–0.0047	0.0174	0.785	–0.0388	0.0293
2017	–0.2015	0.0163	0.000***	–0.2334	–0.1696
2018	–0.5440	0.0362	0.000***	–0.6149	–0.4731
2019	–0.1538	0.0162	0.000***	–0.1855	–0.1221
2023	–0.3444	0.0159	0.000***	–0.3757	–0.3132
Constant	–0.0975	0.0209	0.000***	–0.1384	–0.0566
F statistic			138.40***		
R^2			0.0064		
N. Obs.			200,532		

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table C.13: Impact of specific tree cover loss on trust in the army in LAC, 2008–2023

	β	*SE*	*p*	*95% CI*	
Specific tree cover loss	–0.0279	0.0052	0.000***	–0.0382	–0.0177
GDP per capita	–0.0052	0.0050	0.300	–0.0150	0.0046
Democracy index	0.0255	0.0079	0.001***	0.0100	0.0411
Corruption perception index	0.0925	0.0146	0.000***	0.0637	0.1212
Urbanization rate	–0.0314	0.0038	0.000***	–0.0390	–0.0239
Countries					
Bolivia	0.0817	0.0311	0.009***	0.0207	0.1428
Brazil	0.4018	0.0211	0.000***	0.3605	0.4432
Chile	0.0786	0.0394	0.046**	0.0013	0.1559
Colombia	0.2250	0.0208	0.000***	0.1842	0.2657
Dominican Republic	0.2460	0.0216	0.000***	0.2038	0.2883
Ecuador	0.4329	0.0232	0.000***	0.3875	0.4784
El Salvador	0.3722	0.0250	0.000***	0.3232	0.4212
Guatemala	0.3680	0.0275	0.000***	0.3140	0.4220
Guyana	0.2472	0.0287	0.000***	0.1909	0.3035
Honduras	0.2450	0.0264	0.000***	0.1933	0.2967
Jamaica	0.2176	0.0218	0.000***	0.1749	0.2602
Mexico	0.4492	0.0206	0.000***	0.4087	0.4896
Nicaragua	0.3962	0.0312	0.000***	0.3351	0.4573
Paraguay	0.2230	0.0240	0.000***	0.1759	0.2701
Peru	0.1265	0.0205	0.000***	0.0863	0.1667
Uruguay	–0.0565	0.0448	0.207	–0.1444	0.0313
Venezuela	0.1369	0.0340	0.000***	0.0703	0.2035
Years					
2009	0.2424	0.0310	0.000***	0.1817	0.3031
2010	0.0967	0.0112	0.000***	0.0748	0.1186
2011	0.1823	0.0302	0.000***	0.1230	0.2416
2012	0.0760	0.0172	0.000***	0.0423	0.1096
2013	1.1890	0.3018	0.000***	0.5973	1.7807
2014	0.0470	0.0129	0.000***	0.0217	0.0722
2017	0.1432	0.0118	0.000***	0.1200	0.1663
2018	–0.0615	0.0324	0.058*	–0.1251	0.0021
2019	0.0205	0.0122	0.093*	–0.0034	0.0445
2023	–0.0151	0.0126	0.231	–0.0399	0.0096
Constant	–0.3035	0.0197	0.000***	–0.3420	–0.2649
F statistic			72.50***		
R^2			0.0116		
N. Obs.			197,406		

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table C.14: Impact of specific tree cover loss on trust in elections in LAC, 2008–2023

	β	*SE*	*p*	*95% CI*	
Specific tree cover loss	–0.0240	0.0056	0.000***	–0.0350	–0.0129
GDP per capita	0.0001	0.0049	0.976	–0.0095	0.0098
Democracy index	–0.0471	0.0077	0.000***	–0.0622	–0.0319
Corruption perception index	0.0943	0.0151	0.000***	0.0647	0.1240
Urbanization rate	–0.0237	0.0038	0.000***	–0.0312	–0.0162
Countries					
Bolivia	–0.1167	0.0279	0.000***	–0.1715	–0.0620
Brazil	–0.1693	0.0206	0.000***	–0.2097	–0.1289
Chile	0.0472	0.0401	0.239	–0.0314	0.1259
Colombia	–0.2166	0.0190	0.000***	–0.2540	–0.1793
Dominican Republic	–0.0582	0.0198	0.003***	–0.0970	–0.0194
Ecuador	–0.0695	0.0211	0.001***	–0.1109	–0.0281
El Salvador	0.0132	0.0222	0.553	–0.0304	0.0568
Guatemala	–0.1408	0.0237	0.000***	–0.1872	–0.0944
Guyana	–0.1620	0.0334	0.000***	–0.2275	–0.0964
Honduras	–0.2456	0.0257	0.000***	–0.2960	–0.1951
Jamaica	–0.2490	0.0191	0.000***	–0.2864	–0.2115
Mexico	–0.0884	0.0200	0.000***	–0.1277	–0.0491
Nicaragua	–0.0829	0.0289	0.004***	–0.1396	–0.0263
Paraguay	–0.1432	0.0227	0.000***	–0.1877	–0.0986
Peru	–0.1127	0.0182	0.000***	–0.1484	–0.0770
Uruguay	0.4927	0.0438	0.000***	0.4069	0.5786
Venezuela	0.0794	0.0328	0.015**	0.0152	0.1437
Years					
2009	0.1047	0.0302	0.001***	0.0455	0.1640
2010	0.0740	0.0129	0.000***	0.0487	0.0992
2011	0.0533	0.0320	0.097*	–0.0096	0.1161
2012	0.0141	0.0167	0.398	–0.0186	0.0469
2013	0.8193	0.2233	0.000***	0.3814	1.2571
2014	–0.0998	0.0133	0.000***	–0.1258	–0.0738
2017	–0.0988	0.0119	0.000***	–0.1222	–0.0754
2018	–0.1947	0.0326	0.000***	–0.2586	–0.1308
2019	–0.1454	0.0124	0.000***	–0.1698	–0.1210
2023	–0.1951	0.0127	0.000***	–0.2199	–0.1701
Constant	0.1159	0.0170	0.000***	0.0825	0.1493
F statistic			198.84***		
R^2			0.0086		
N. Obs.			197,925		

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table C.15: Impact of specific tree cover loss on trust in congress in LAC, 2008–2023

	β	*SE*	*P*	*95% CI*	
Specific tree cover loss	–0.0205	0.0046	0.000***	–0.0296	–0.0115
GDP per capita	–0.0074	0.0041	0.072*	–0.0154	0.0006
Democracy index	–0.0694	0.0066	0.000***	–0.0824	–0.0564
Corruption perception index	0.1580	0.0143	0.000***	0.1300	0.1860
Urbanization rate	–0.0213	0.0033	0.000***	–0.0277	–0.0149
Countries					
Bolivia	–0.0295	0.0227	0.193	–0.0740	0.0150
Brazil	–0.1565	0.0159	0.000***	–0.1878	–0.1252
Chile	–0.3772	0.0374	0.000***	–0.4504	–0.3039
Colombia	–0.0407	0.0157	0.009***	–0.0715	–0.0100
Dominican Republic	0.0766	0.0153	0.000***	0.0466	0.1067
Ecuador	–0.1459	0.0179	0.000***	–0.1810	–0.1109
El Salvador	0.0030	0.0215	0.889	–0.0392	0.0452
Guatemala	–0.1099	0.0197	0.000***	–0.1486	–0.0713
Guyana	0.1449	0.0249	0.000***	0.0960	0.1937
Honduras	–0.0180	0.0206	0.382	–0.0584	0.0223
Jamaica	–0.1670	0.0170	0.000***	–0.2003	–0.1337
Mexico	0.1586	0.0148	0.000***	0.1296	0.1877
Nicaragua	–0.0070	0.0235	0.764	–0.0531	0.0390
Paraguay	–0.1120	0.0181	0.000***	–0.1475	–0.0765
Peru	–0.4033	0.0148	0.000***	–0.4324	–0.3742
Uruguay	–0.0420	0.0406	0.301	–0.1216	0.0377
Venezuela	0.0829	0.0257	0.001***	0.0326	0.1333
Years					
2009	0.1074	0.0326	0.001***	0.0434	0.1714
2010	0.1246	0.0102	0.000***	0.1046	0.1446
2011	0.1712	0.0263	0.000***	0.1196	0.2227
2012	0.0748	0.0141	0.000***	0.0472	0.1024
2013	1.7605	0.3567	0.000***	1.0612	2.4598
2014	–0.0311	0.0111	0.005***	–0.0528	–0.0094
2017	0.0310	0.0105	0.003***	0.0105	0.0516
2018	–0.0773	0.0274	0.005***	–0.1311	–0.0235
2019	–0.0465	0.0107	0.000***	–0.0675	–0.0254
2023	–0.0961	0.0107	0.000***	–0.1171	–0.0752
Constant	0.0392	0.0133	0.003***	0.0131	0.0652
F statistic			138.37***		
R^2			0.0121		
N. Obs.			194,479		

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table C.16: Impact of specific tree cover loss on trust in municipality in LAC, 2008–2023

	β	*SE*	*p*	*95% CI*	
Specific tree cover loss	0.0121	0.0062	0.050*	–0.0000	0.0243
GDP per capita	–0.0352	0.0056	0.000***	–0.0463	–0.0242
Democracy index	–0.0432	0.0083	0.000***	–0.0595	–0.0269
Corruption perception index	0.0603	0.0165	0.000***	0.0280	0.0926
Urbanization rate	–0.0127	0.0042	0.003***	–0.0210	–0.0044
Countries					
Bolivia	–0.1002	0.0341	0.003***	–0.1672	–0.0333
Brazil	–0.0915	0.0234	0.000***	–0.1373	–0.0457
Chile	0.1638	0.0451	0.000***	0.0754	0.2523
Colombia	–0.0277	0.0233	0.235	–0.0735	0.0180
Dominican Republic	0.0105	0.0241	0.661	–0.0367	0.0578
Ecuador	–0.0019	0.0245	0.939	–0.0500	0.0463
El Salvador	0.2150	0.0261	0.000***	0.1639	0.2662
Guatemala	–0.0083	0.0270	0.758	–0.0613	0.0446
Guyana	–0.0511	0.0301	0.090*	–0.1102	0.0080
Honduras	0.0589	0.0291	0.044**	0.0017	0.1160
Jamaica	–0.2161	0.0217	0.000***	–0.2587	–0.1735
Mexico	0.1637	0.0213	0.000***	0.1219	0.2055
Nicaragua	–0.0538	0.0326	0.099*	–0.1178	0.0102
Paraguay	0.0793	0.0264	0.003***	0.0275	0.1312
Peru	–0.2324	0.0221	0.000***	–0.2757	–0.1891
Uruguay	0.0406	0.0477	0.396	–0.0530	0.1342
Venezuela	0.1686	0.0324	0.000***	0.1050	0.2321
Years					
2009	0.0457	0.0412	0.268	–0.0352	0.1265
2010	0.0213	0.0126	0.089*	–0.0033	0.0460
2011	–0.1003	0.0358	0.005***	–0.1706	–0.0300
2012	0.0077	0.0199	0.700	–0.0313	0.0466
2013	0.8968	0.2325	0.000***	0.4411	1.3526
2014	–0.0706	0.0140	0.000***	–0.0981	–0.0430
2017	–0.0529	0.0126	0.000***	–0.0777	–0.0282
2018	–0.0155	0.0359	0.667	–0.0859	0.0549
2019	–0.0783	0.0132	0.000***	–0.1042	–0.0524
2023	–0.1201	0.0138	0.000***	–0.1472	–0.0931
Constant	0.0276	0.0194	0.155	–0.0104	0.0656
F statistic			68.13***		
R^2			0.0047		
N. Obs.			198,596		

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table C.17: Impact of specific tree cover loss on trust in political parties in LAC, 2008–2023

	β	*SE*	*p*	*95% CI*	
Specific tree cover loss	–0.0217	0.0050	0.000***	–0.0315	–0.0119
GDP per capita	–0.0035	0.0049	0.471	–0.0130	0.0060
Democracy index	–0.0645	0.0076	0.000***	–0.0795	–0.0495
Corruption perception index	0.1909	0.0149	0.000***	0.1617	0.220
Urbanization rate	–0.0145	0.0036	0.000***	–0.0216	–0.0074
Countries					
Bolivia	–0.0819	0.0302	0.007***	–0.1411	–0.0227
Brazil	–0.1386	0.0180	0.000***	–0.1739	–0.1034
Chile	–0.4311	0.0378	0.000***	–0.5053	–0.3570
Colombia	–0.0356	0.0184	0.053*	–0.0718	0.0005
Dominican Republic	0.0566	0.0175	0.001***	0.0224	0.0909
Ecuador	–0.0755	0.0189	0.000***	–0.1125	–0.0385
El Salvador	0.0256	0.0202	0.207	–0.0141	0.0653
Guatemala	–0.0102	0.0204	0.617	–0.0502	0.0298
Guyana	0.3709	0.0282	0.000***	0.3156	0.4262
Honduras	0.1276	0.0226	0.000***	0.0832	0.1720
Jamaica	0.0485	0.0176	0.006***	0.0140	0.0829
Mexico	0.0943	0.0173	0.000***	0.0603	0.1282
Nicaragua	0.0946	0.0269	0.000***	0.0419	0.1473
Paraguay	0.0399	0.0200	0.046**	0.0007	0.0790
Peru	–0.2030	0.0159	0.000***	–0.2342	–0.1718
Uruguay	–0.1048	0.0418	0.012**	–0.1867	–0.0228
Venezuela	0.2396	0.0283	0.000***	0.1841	0.2950
Years					
2009	0.0640	0.0379	0.091*	–0.0102	0.1383
2010	0.0601	0.0113	0.000***	0.0380	0.0822
2011	0.0568	0.0337	0.091*	–0.0091	0.1229
2012	0.0706	0.0185	0.000***	0.0344	0.1068
2013	0.9573	0.3161	0.002***	0.3376	1.5771
2014	–0.1140	0.0116	0.000***	–0.1367	–0.0912
2017	–0.1226	0.0108	0.000***	–0.1437	–0.1015
2018	–0.1534	0.0263	0.000***	–0.2050	–0.1018
2019	–0.1392	0.0112	0.000***	–0.1612	–0.1173
2023	–0.1561	0.0119	0.000***	–0.1794	–0.1328
Constant	0.0555	0.0147	0.000***	0.0266	0.0844
F statistic			94.05***		
R^2			0.0051		
N. Obs.			198,108		

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table C.18: Impact of specific tree cover loss on trust in police in LAC, 2008–2023

	β	*SE*	*p*	*95% CI*	
Specific tree cover loss	–0.0002	0.0061	0.975	–0.0121	0.0117
GDP per capita	0.0018	0.0055	0.736	–0.0089	0.0126
Democracy index	0.0188	0.0084	0.026**	0.0022	0.0354
Corruption perception index	0.1302	0.0164	0.000***	0.0980	0.1623
Urbanization rate	–0.0084	0.0041	0.043**	–0.0165	–0.0002
Countries					
Bolivia	0.0051	0.0326	0.874	–0.0587	0.0690
Brazil	0.2453	0.0226	0.000***	0.2009	0.2897
Chile	0.2188	0.0435	0.000***	0.1335	0.3041
Colombia	0.2430	0.0220	0.000***	0.1999	0.2861
Dominican Republic	–0.0302	0.0225	0.179	–0.0742	0.0138
Ecuador	0.3115	0.0240	0.000***	0.2645	0.3585
El Salvador	0.3717	0.0277	0.000***	0.3174	0.4260
Guatemala	0.0315	0.0274	0.251	–0.0223	0.0853
Guyana	0.1445	0.0328	0.000***	0.0803	0.2088
Honduras	0.1756	0.0288	0.000***	0.1192	0.2320
Jamaica	–0.0702	0.0223	0.002***	–0.1139	–0.0266
Mexico	–0.0512	0.0212	0.015**	–0.0927	–0.0098
Nicaragua	0.4407	0.0305	0.000***	0.3810	0.5004
Paraguay	0.0290	0.0254	0.254	–0.0208	0.0788
Peru	–0.0077	0.0211	0.717	–0.0491	0.0338
Uruguay	0.0161	0.0487	0.741	–0.0793	0.1115
Venezuela	0.0142	0.0341	0.678	–0.0528	0.0811
Years					
2009	0.0915	0.0394	0.020**	0.0141	0.1688
2010	0.0294	0.0123	0.017**	0.0053	0.0535
2011	0.1432	0.0394	0.000***	0.0661	0.2204
2012	0.0419	0.0186	0.024**	0.0055	0.0783
2013	0.7395	0.2669	0.006***	0.2163	1.2628
2014	–0.0146	0.0136	0.283	–0.0413	0.0121
2017	0.0045	0.0125	0.721	–0.0200	0.0289
2018	–0.0807	0.0349	0.021**	–0.1491	–0.0122
2019	–0.0079	0.0132	0.551	–0.0338	0.0180
2023	–0.0287	0.0135	0.034**	–0.0552	–0.0022
Constant	–0.1367	0.0199	0.000***	–0.1758	–0.0977
F statistic			147.48***		
R^2			0.0120		
N. Obs.			200,532		

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table C.19: Impact of specific tree cover loss on trust in president in LAC, 2008–2023

	β	*SE*	*p*	*95% CI*	
Specific tree cover loss	–0.0022	0.0068	0.740	–0.0155	0.01105
GDP per capita	–0.0147	0.0063	0.020**	–0.0272	–0.0023
Democracy index	–0.0914	0.0100	0.000***	–0.1111	–0.0718
Corruption perception index	–0.0210	0.0200	0.294	–0.0601	0.0182
Urbanization rate	–0.0310	0.0049	0.000***	–0.0407	–0.0213
Countries					
Bolivia	0.0152	0.0335	0.649	–0.0505	0.0810
Brazil	0.3380	0.0250	0.000***	0.2889	0.3871
Chile	0.4541	0.0507	0.000***	0.3548	0.5534
Colombia	0.3262	0.0255	0.000***	0.2763	0.3762
Dominican Republic	0.4132	0.0263	0.000***	0.3615	0.4648
Ecuador	0.1799	0.0254	0.000***	0.1300	0.2298
El Salvador	0.2632	0.0326	0.000***	0.1994	0.3270
Guatemala	–0.1080	0.0272	0.000***	–0.1614	–0.0546
Guyana	0.0920	0.0394	0.020**	0.0148	0.1693
Honduras	–0.0481	0.0291	0.099*	–0.1052	0.0090
Jamaica	0.2115	0.0249	0.000***	0.1627	0.2603
Mexico	0.2888	0.0240	0.000***	0.2418	0.3359
Nicaragua	–0.0295	0.0396	0.457	–0.1072	0.0482
Paraguay	–0.0523	0.0281	0.063	–0.1074	0.0028
Peru	–0.0741	0.0221	0.001***	–0.1174	–0.0307
Uruguay	0.6436	0.0544	0.000***	0.5369	0.7503
Venezuela	–0.0884	0.0376	0.019**	–0.1621	–0.0147
Years					
2009	0.2953	0.0427	0.000***	0.2116	0.3790
2010	0.1052	0.0156	0.000***	0.0745	0.1358
2011	0.1550	0.0388	0.000***	0.0790	0.2310
2012	–0.0061	0.0213	0.773	–0.0479	0.0356
2013	0.2552	0.1714	0.137	–0.0808	0.5913
2014	–0.0032	0.0176	0.856	–0.0376	0.0312
2017	–0.2051	0.0161	0.000***	–0.2366	–0.1735
2018	–0.5462	0.0361	0.000***	–0.6171	–0.4754
2019	–0.1532	0.0164	0.000***	–0.1853	–0.1211
2023	–0.3427	0.0162	0.000***	–0.3745	–0.3109
Constant	–0.0996	0.0209	0.000***	–0.1405	–0.0586
F statistic			138.33***		
R^2			0.0063		
N. Obs.			200,532		

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

Table C.20: Between-within regression of institutional trust on specific tree cover loss

DV: Institutional trust	*β*	*SE*	*p*	*95% CI*	
Within-country (deviation)					
Yearly tree cover loss	–0.0139	0.0047	0.003	–0.0231	–0.0047
Between-country (mean)					
Average tree cover loss	–0.1073	0.0250	0.000	–0.1563	–0.0584
GDP per capita	–0.0166	0.0065	0.011	–0.0294	–0.0037
Democracy index	–0.0721	0.0111	0.000	–0.0938	–0.0504
Corruption perception index	0.1846	0.0208	0.000	0.1438	0.2254
Urbanization rate	–0.0348	0.0053	0.000	–0.0452	–0.0244
Countries					
Bolivia	–0.1480	0.0364	0.000	–0.2193	–0.0767
Brazil	–0.0114	0.0309	0.712	–0.0720	0.0492
Chile	–0.0863	0.0635	0.175	–0.2108	0.0383
Colombia	–0.0248	0.0370	0.502	–0.0973	0.0476
Dominican Republic	0.1121	0.0224	0.000	0.0681	0.1561
Ecuador	–0.0029	0.0304	0.924	–0.0625	0.0567
El Salvador	0.1924	0.0381	0.000	0.1177	0.2671
Guatemala	0.0731	0.0494	0.139	–0.0238	0.1700
Guyana	0.0138	0.0531	0.795	–0.0903	0.1180
Honduras	0.1120	0.0448	0.012	0.0242	0.1998
Jamaica	–0.2088	0.0415	0.000	–0.2902	–0.1274
Mexico	0.1628	0.0246	0.000	0.1146	0.2110
Nicaragua	0.2252	0.0482	0.000	0.1308	0.3197
Paraguay	0.1033	0.0511	0.043	0.0030	0.2035
Peru	–0.3928	0.0361	0.000	–0.4636	–0.3221
Uruguay	0.3644	0.0571	0.000	0.2523	0.4764
Years					
2009	0.2412	0.0498	0.000	0.1434	0.3389
2010	0.1383	0.0161	0.000	0.1068	0.1699
2011	0.1774	0.0450	0.000	0.0892	0.2656
2012	0.0864	0.0229	0.000	0.0415	0.1313
2013	–0.2729	0.0481	0.000	–0.3673	–0.1786
2014	–0.0680	0.0178	0.000	–0.1029	–0.0332
2017	–0.0684	0.0164	0.000	–0.1006	–0.0362
2018	–0.2767	0.0461	0.000	–0.3671	–0.1863
2019	–0.1364	0.0171	0.000	–0.1699	–0.1030
2023	–0.2294	0.0173	0.000	–0.2633	–0.1955
Constant	0.0043	0.0217	0.842	–0.0382	0.0468
F statistic			113.82***		
R^2			0.0064		
N. Obs.			184,989		

Notes: Model includes country and year fixed effects. Reference category for country is Argentina; for year is 2008.
*The symbols ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.*

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