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Distribution Sensitive Policy Analysis based on WELLBYs: Constructing a Prioritarian Social Welfare Function through Causal Evidence on Life Satisfaction

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Abstract

This dissertation examines the implications of prioritizing those worse-off in policy analysis, being the first study to construct a Prioritarian Social Welfare Function (SWF) using life satisfaction as a welfare measure. As such, the study begins with a comprehensive theoretical analysis, justifying a focus on the improvements for those worse-off based on the claims-based fairness concept. It then advocates for Prioritarianism over Egalitarianism, particularly in light of the levelling-down objection, and ultimately justifies life satisfaction as a welfare measure as it aligns most closely with democratic principles.

Building on this theoretical foundation, I analyzed the impact of Victoria's second COVID-19 lockdown (July-October, 2020) on life satisfaction, utilizing Australia's major household panel survey (HILDA) and a difference-in-differences approach to isolate the policy's effect from the general pandemic by comparing changes in life satisfaction over time in the treatment group (Victoria, August–November, 2020) with changes over time in the control group (all other Australian states, August–November, 2020).

The results indicate a highly significant negative impact, with a decrease of 0.0303 points on a 0-10 Likert scale (95% CI -0.0486 to -0.0120, $p = 0.006$). Further analyses reveal a disproportionately large effect on individuals with lower life satisfaction, poor mental health, and younger age (15-19 years), highlighting the need for targeted complementary wellbeing interventions in the event of future lockdowns.

Ultimately, the difference-in-differences design was used to construct a Prioritarian SWF, contrasting the modeled social welfare of Victoria in 2020 under the lockdown scenario (13,775,625 Prioritarian WELLBYs) to a Business-as-Usual scenario (52,366,212 Prioritarian WELLBYs). In conclusion, while the lockdown aimed to protect public health, the analysis suggests that the wellbeing decline outweighed the benefits of reduced premature deaths. In turn, this research offers guidance for prioritizing those worse-off in future policy analyses and adds vital evidence to the global pandemic discourse.

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1 Introduction

Neoclassical economics assumes rational agents maximize welfare without accounting for fairness or inequality concerns. In contrast, behavioral economics provides substantial evidence about fairness (Rabin, 1993; Fehr & Schmidt, 1999) and inequality-aversion (Clark & D'Ambrosio, 2015; Hurley et al., 2020; Robson et al., 2024), demonstrating an inherent preference for reducing disparities regarding income, health, and life expectancy, rather than solely maximizing societal totals. Nevertheless, a preference for equality usually involves a trade-off with efficiency, requiring policy decisions on *whether*, and to *what extent*, the welfare of those worse-off should be prioritized in accounting for inequal policy outcomes.

1.1 Background

The trade-off between efficiency and a more equitable distribution of welfare that a society, a social planner, or a policy analyst is willing to make can be formally represented through a Social Welfare Function (SWF) (Dolan & Tsuchiya, 2011). The general framework of SWFs originated with Abram Bergson (1938) and was further developed by Paul Samuelson (1947), who added a mathematical foundation to demonstrate its applicability to a range of economic policies. Kenneth Arrow (1951) highlighted significant challenges through his impossibility theorem which demonstrated difficulties in constructing a SWF that meets all desirable criteria without engaging in interpersonal comparisons of ordinal preferences. Nevertheless, Amartya Sen (1970) revitalized the concept by proposing that the social ranking of outcomes should depend on individuals' wellbeing numbers rather than their preference orderings. Specifically, Sen introduced a functional relation from a given wellbeing measure to an outcome ranking.

Those outcome rankings are fundamentally rooted in distinct philosophical theories that guide the evaluation of societal welfare and the theory of Utilitarianism has been most dominant since decades (Eggleston and Miller, 2014; Brandt 1979; Broome 1991; Goodin 1995; Harsanyi 1977; Singer 2011). In fact, the SWF framework can be seen as a generalization of Classical Utilitarianism[1], a moral theory proposed by philosophers including Jeremy Bentham (1789) and John Stuart Mill (1863) which asserts, that an act is morally right if, and only if, it maximizes total pleasure minus pain. As such, Classical Utilitarianism implies four key concepts (Adler,

[1] The difference between Classical Utilitarianism and Utilitarianism is that Utilitarianism allows for modifications in Hedonism. Preference Utilitarianism has been most dominant.

2019, p.7-40) for evaluating moral acts: First, Consequentialism; which posits that actions are evaluated based on their outcomes. Second, Welfarism; which determines individual wellbeing as the only morally relevant metric. Third, Sum-Ranking; which aggregates total wellbeing in a society across individuals based on a simple summation. Ultimately, fourth, Hedonism; defining wellbeing as pleasure minus pain. The SWF framework, in turn, is specifically developed for policy evaluations and, as a more generalized version of Classical Utilitarianism, retains the two concepts Consequentialism and Welfarism thereby establishes policy evaluation based on outcomes using individual wellbeing as the only morally relevant criteria. In addition to Welfare Consequentialism[2], the SWF framework crucially allows for modifications in Sum-Ranking and Hedonism, enabling the introduction of different ranking rules E and alternative welfare measures. In turn, integrating alternative ranking rules, such as those that prioritize those worse-off and integrate an inequality-aversion, enables the SWF framework to formally represent contrary philosophical theories that guide the evaluation of social welfare, extending beyond its (Classical) Utilitarianism origins and allowing to express alternative normative views.

1.2 Motivation

Two opposing philosophical theories that incorporate an inequality-aversion are Prioritarianism and Egalitarianism. Although the theories of Prioritarianism and Egalitarianism are well established, its practical applications remain rare, and most policy analyses employed are still ignoring an inequality-aversion (Adler & Norheim, 2022). Prioritarianism gained most of its prominence after Derek Parfit's 1991 Lindley Lecture[3] and has been supported by several economists and philosophers since then. Parfit's work built on discussions of equality, such as those by Thomas Nagel (1979, 1991) who significantly contributed to the field of distributive justice. Both Parfit’s and Nagel's contributions highlight how ethical theories can incorporate a concern for those worse-off by addressing differences between Utilitarianism, Prioritarianism, and Egalitarianism.

[2] Together, Welfarism and Consequentialism culminate in Welfare Consequentialism, which posits that the wellbeing outcome is the sole criterion of moral relevance.
[3] The Lindley Lecture was later summarized and published in: Parfit, D. (1997). Equality and Priority. Ratio, 10(3), 202–221. https://doi.org/10.1111/1467-9329.00041. This paper is a shortened version of the 1991 Lindley Lecture “Equality or Priority?” (42 pp.), published by the University of Kansas in 1995.

In recent years, Matthew Adler and colleagues have advanced a project known as *Prioritarianism in Practice* which justifies and applies Prioritarian SWFs for policy analyses. These applications, thus far, have applied Prioritarianism in areas such as health (Cookson et al., 2022), tax (Tuomala & Weinzierl, 2022), climate change (Ferranna & Fleurbaey, 2022), and education (Ooghe, 2022), employing quality-adjusted life years, value of a statistical life, consumption, and educational achievements as welfare measures. This dissertation aims to extend the *Prioritarianism in Practice* project by being the first to construct a Prioritarian SWF using life satisfaction as a welfare measurement. Life satisfaction respects individual judgments and enhances policy responsiveness, aligning with democratic principles and effectively capturing the needs of citizens. Following Parfit, I argue that moral importance should inversely relate to suffering, with moral weight increasing as life satisfaction decreases.

In turn, this thesis progresses as follows: Chapter 2 discusses the primary philosophical approaches to social welfare analysis, namely Utilitarianism, Prioritarianism, and Egalitarianism. It examines perspectives on fairness and compares priority with equality, ultimately making a case for the Prioritarian Atkinson SWF. Chapter 3 argues for the use of subjective wellbeing for policy evaluation. It advocates for WELLBYs as a measure for social welfare and revises the necessary intra- and interpersonal comparison condition for the application of life satisfaction within the SWF framework. Chapter 4 presents an empirical construction of an Atkinson SWF in the context of the COVID-19 lockdown policy in Victoria, Australia. The study is, to my knowledge, the first to isolate the causal impact of a COVID-19 lockdown on life satisfaction. The findings reveal a highly significant negative effects of -0.0303 points (95% CI -0.0486 to -0.0120 p = 0.006) on life satisfaction measured on a 0-10 scale and are used to construct a SWF by contrasting the lockdown policy to a Business-as-Usual scenario. Chapter 5 critically examines the limitations of both the theoretical foundations of SWFs, Prioritarianism, and life satisfaction, as well as the methodological challenges in policy analysis. It ultimately concludes with a discussion on policy implications and suggestions for future research.

2 Utilitarianism, Prioritarianism, or Egalitarianism?

2.1 Fairness

The initial question regarding *whether* and to *what extent* the welfare of those worse-off should be prioritized in addressing inequal policy outcomes fundamentally pertains to considerations of fairness and moral intuition. The SWF as a normative tool for policy assessment should be *fair* to each individual, but what does this mean?

Consider the following two scenarios. In the first outcome O, half the population experiences low life satisfaction, living a life in misery due to high-stress work, poor living conditions, and lack of healthcare, while the other half enjoys high life satisfaction with a universal income, comfortable living conditions, and excellent healthcare. In an alternative outcome O^*, life satisfaction is perfectly equalized, with everyone enjoying a moderate level.

The Utilitarian SWF is indifferent between O and O^*. However, intuitively, this seems quite problematic, or, unfair, as the significant disparity in outcome O highlights substantial inequality. Notwithstanding this problematic intuition, a fairness-based case for Utilitarianism has been developed by John Harsanyi (1953, 1955) which applies the veil-of-ignorance by imagining a self-interested person who ranks outcomes based on the assumption that they have an equal probability of assuming the identity of each person in the population. As such, this perspective leads to a Utilitarian ranking of outcomes, being indifferent between the discussed outcomes O and O^*.

Nevertheless, the veil-of-ignorance, most famously associated with John Rawls' *A Theory of Justice* (1971), was indeed applied by him as well, but under a condition of complete ignorance regarding whose identity the self-interested person might be, rather than by assigning equal probabilities. Using Rawls' notion of complete ignorance does not lead to a Utilitarian ranking of outcomes but prioritizes those worse-off. In spite of that, it remains unclear whether Rawls' version of the veil-of-ignorance is more or less plausible than Harsanyi's. Therefore, Adler (2019, p. 115-160) concludes that the most effective defense for emphasizing those at the lower of the distribution is to advocate for an alternative conception of fairness.

Beyond the veil-of-ignorance, a concept arguing for Prioritarianism and Egalitarianism over Utilitarianism is the "claims-based" conception of fairness, as articulated by Thomas Nagel (1979) and further developed in Adler (2019, p. 115-160). Claims-based fairness states that if an individual has higher wellbeing in *w* than in *v*, this gives him/her a claim to *w* over *v*. Imagine a person Lars with initial wellbeing lower than that of Clara, moreover a conflicting claim arises such that Lars is better off in *w*, but Clara in *v*. This results in Lars having a claim to *w* over *v* while Clara has a claim to *v* over *w.* Furthermore, moving from *w* to *v* constitutes a pure gap-closing transfer of wellbeing from Clara to Lars, reducing the wellbeing disparity between them. Utilitarianism treats all claims equally, thus, ignoring any wellbeing disparities. In contrast, Prioritarian and Egalitarian SWFs acknowledge the disparities between individuals' distributional positions and prioritize those at the lower end through stronger claims such as Lars'.

To illustrate, if $w = (w(\cdot)_1, w(\cdot)_2, w(\cdot)_3, \ldots, w(\cdot)_n)$ and $v = (v(\cdot)_1, v(\cdot)_2, v(\cdot)_3, \ldots, v(\cdot)_n)$ are wellbeing vectors, then *i* has a claim to *w* over *v* if, and only if, $w(\cdot)_i > v(\cdot)_i$. The strength of the claim is given as the difference $w(\cdot)_i$ - $v(\cdot)_i$, so that the claim of *i* to *w* over *v* is:

$$c_i(w(\cdot)_i | v(\cdot)_i) = max\{w(\cdot)_i - v(\cdot)_i, 0\} = \begin{cases} w(\cdot)_i - v(\cdot)_i & if\ w(\cdot)_i > v(\cdot)_i \\ 0 & if\ w(\cdot)_i \leq v(\cdot)_i \end{cases}$$

In the context of SWFs, the claims-based fairness concept is formally represented through the Pigou-Dalton Axiom, which states that if one person is better off than a second in *w*, and if *w* is reached from *v* by a pure, gap-diminishing transfer of wellbeing from the first person to the second, leaving everyone else unaffected. Then *w* is morally better, or fairer, than *v*. To illustrate, this means that the distribution of *w* (7, 15, 17, 6) is preferred over the distribution of *v* (7, 12, 20, 6), as *w* is reached by a pure, gap-diminishing transfer from *v*: 20 (*v)* -> 17 (*w*) and 12 (*v*) ->15 (*w*). While Prioritarian and Egalitarian SWFs satisfy the Pigou-Dalton Axiom, Utilitarian SWFs do not, so that both outcomes *w* and *v* are evaluated as equally good, or equally fair, following Utilitarianism.

Proponents of Utilitarian SWFs may adhere to Harsanyi's veil-of-ignorance while advocates of Prioritarian or Egalitarian SWFs can reason their ethical arguments in the claims-based concept of fairness or in Rawls' version of the veil-of-ignorance. Unfortunately, this alone does not lead to a stable answer regarding *whether* and to *what extent* the welfare of those worse-off should be prioritized in addressing inequal policy outcomes. Nevertheless, in philosophical reasoning, strong intuitions about specific cases, such as the comparison between *O* and *O**, or *w* and *v*, are a legitimate source of ethical argument.

"In seeking her point of reflective equilibrium, the deliberator tries to harmonize both the general principles to which she is provisionally committed and her intuitions about specific cases." (Adler 2019, p. 124)

I argue that the claims-based conception of fairness aligns with strong intuitions, evidentially supported by empirical research on preferences for fairness and inequality-aversion (Clark & D'Ambrosio, 2015; Hurley et al., 2020; Robson et al., 2024), which undermine the ethical significance of a sensitivity to distribution in policy evaluations. Consequently, this conception should be adopted, naturally leading to the application of SWFs satisfying the Pigou-Dalton Axiom, such as Prioritarian or Egalitarian. In turn, the initial question regarding <u>*whether*</u> and to <u>*what extent*</u> the welfare of those worse-off should be prioritized can yet be partially answered by stating: *yes, the welfare of those worse-off should be prioritized.*

2.2 Priority vs Equality

Individuals at the lower end of the distribution hold stronger claims, warranting their preferential consideration. The type of claim, however, is a different between a Prioritarian and an Egalitarian perspective.

Egalitarianism emphasizes comparative fairness, where the ethical significance of changes in an individual's wellbeing depends on their relative standing within the population. Philosopher Larry Temkin (2003) asserts that morality must address concerns of comparative fairness arguing that it is inherently unjust for individuals to be worse-off than others through no fault of their own. In contrast, Prioritarianism posits that benefiting people matters more the worse-off these people are, focusing on absolute wellbeing rather than relative standings. Two analogies illustrate this distinction. Consider that people at higher altitudes find it harder to breathe, an issue of absolute altitude. Even if no one were at a lower altitude, they would still struggle to breathe. Conversely, shorter people at a concert find it harder to see because of their relative height compared to taller individuals. If there were no taller people, their ability to see would improve. Thus, Prioritarianism, akin to the altitude analogy, values benefiting a person based on their absolute wellbeing. Egalitarianism, similar to the height analogy, values wellbeing improvements based on relative standing compared to others (Adler 2019, p. 115-160).

This distinction is formally represented as the Separability Axiom within Prioritarian SWFs[4] which posits that the ranking of wellbeing vectors is independent of the wellbeing levels of unaffected individuals. That is, if there is a subset of the population each of whose wellbeing level is the same in w as in w^*, then the w/w^* ranking does not depend upon what the wellbeing level of these individuals would be. Separability, thus, has practical benefits as it allows to ignore the wellbeing of all individuals who will be unaffected by a policy decision which can be seen as a first reason to prefer Prioritarian over Egalitarian SWFs.

A second argument for preferring Prioritarian over Egalitarian SWFs is the so-called levelling-down objection. Again, consider two scenarios. In the first scenario S every individual in the population has a life satisfaction score of 7. In the second scenario S^* some have a score of 7 and some have a score of 9. Strong Egalitarians will follow an intrinsic value of equality[5] and argue that the first scenario is better as it is less inequal, thereby implying that levelling-down can be morally right, or fair, which leads Parfit to advocate for Prioritarianism over Egalitarianism.

Moderate Egalitarians confront this objection and state that in some cases the loss of equality is morally outweighed by the benefits. Therefore, Moderate Egalitarian align with a "*pro-tanto goodness*" regarding levelling-down concerns which states that levelling-down is bad all-things-considered, but it is good *pro tanto*, good in a way. This provides Moderate Egalitarians with a response to the levelling-down objection.

Nevertheless, a person-affecting view holds that an act can only be bad if it is bad for someone. A move from S to S^* does not negatively affect any individual. Hence, this move cannot be bad even if it leads to more inequality. Therefore, and as mentioned in the introduction, I argue for following Parfit, by advocating for an inverse relationship between moral importance and

[4] To be precise: The Separability Axiom is associated with Continuous Prioritarian SWF. I am using Continuous Prioritarian SWFs and Prioritarian SWFs as synonyms as the Priority View (Prioritarianism according to Parfit) is mainly associated with Continuous Prioritarian SWFs satisfying the Separability Axiom.

[5] In fact, Egalitarianism combines the two main principles of 1) Equality and 2) Utility, thereby stating that 1) it is bad in itself if some individuals are worse-off than others and 2) it is in itself better if individuals are better off. Prioritarianism does not apply the intrinsic value of Equality and only states that benefiting individuals matters more the worse-off these are.

suffering. That is, the moral weight increases as the life satisfaction of a person decreases, independently of her relative position. In turn, focusing on a distribution sensitivity and absolute rather than relative wellbeing naturally leads to the application of Prioritarian SWFs.

2.3 The Case for the Atkinson SWF

Following the claims-based fairness concept, adopting the Pigou-Dalton Axiom, leads to a choice for Egalitarian and Prioritarian over Utilitarian SWFs, while the levelling-down objection, formally represented within the Separability Axiom, argues for the adoption of Prioritarian over Egalitarian SWFs. Notwithstanding these arguments, one compelling reason for the application of Utilitarian instead of Prioritarian or Egalitarian SWFs still exists: *invariance*.

Utilitarian SWFs satisfy invariance to positive-affine transformation, meaning that their moral rankings of outcomes remain unchanged under any transformation of the kind $x' = c * x + d$ with $c > 0$ and d is a constant. This invariance is a compelling argument in favor of Utilitarian SWFs, as it demonstrates a form of neutrality that eliminates potential biases introduced by alternative welfare baselines or scales and thereby reduces distortions from changes in units or origins of measurement.

Adler (2011, p. 307-404) counters the unique advantage of Utilitarianism's invariance by advocating for the Prioritarian Atkinson SWF, emphasizing that while the Atkinson SWF may not satisfy invariance to positive-affine transformation, it does satisfy ratio-rescaling invariance. This means that the moral ranking of outcomes remains consistent when individual wellbeing is scaled by a constant factor, which is specifically important in the realm of subjective wellbeing due to common rescaling from one Likert scale (e.g. 1-5) to another (e.g. 0-10) (HM Treasury, 2021). The additional axiomatic alignment with the Pigou-Dalton and the Separability Axiom results in a superiority for the Prioritarian Atkinson SWF[6]:

$$Social\ Welfare_{Atkinson} = \sum_{i=1}^{N} g\left(w(\cdot)_i\right) = \left(\sum_{i=1}^{N} \frac{1}{1-\gamma}\, {w(\cdot)_i}^{1-\gamma}\right) with\ \gamma > 0, \gamma \neq 1$$

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[6] This type of SWFs is named after Anthony Atkinson and based on his works about the Atkinson Inequality Index.

Where $w(\cdot)_i$ represents the wellbeing[7] of individual i, N represents the total of individuals in the population of interest, and γ is the inequality-aversion parameter. The Atkinson function $g\ (w(\cdot)_i)$ is characterized by its strictly increasing and strictly concave transformation of individual wellbeing, reflecting a preference for improving the wellbeing of those worse-off. Central is the parameter γ, which determines the degree of inequality-aversion. Choosing $\gamma = 1$ reduces the Atkinson function to a logarithmic transformation reflecting moderate inequality-aversion. This maintains a balance between efficiency and equality, making it suitable for contexts where total wellbeing is still valued relatively high:

$$Social\ Welfare_{Atkinson_{\gamma = 1}} = \sum_{i=1}^{N} ln(\ w(\cdot)_i\ )$$

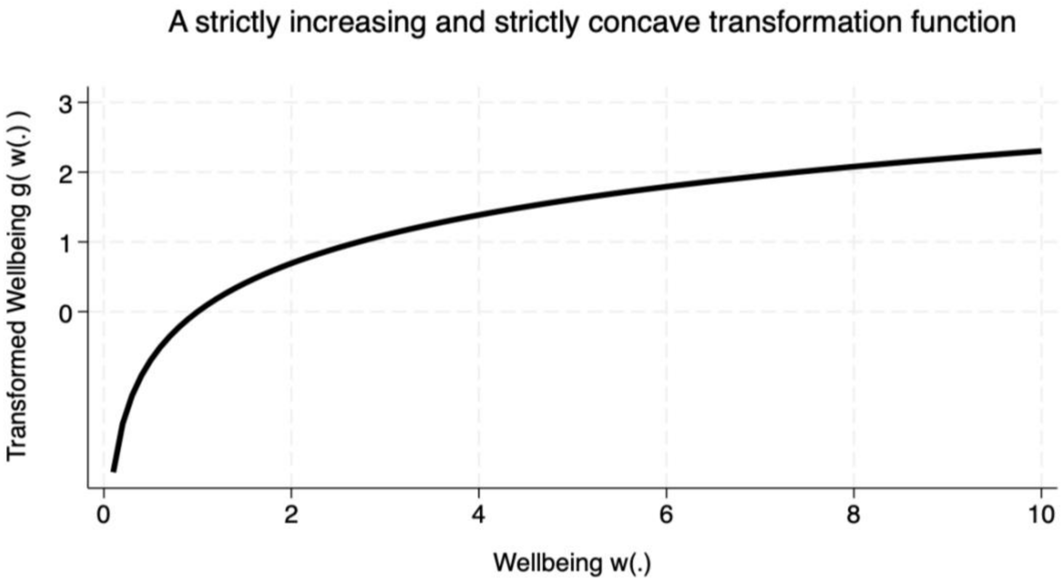

Figure 1. *Concave transformation function. The wellbeing data $w(\cdot)$ and its $ln\ (w(\cdot)\ )$ transformation were generated by me to illustrate the prioritization on improvements for those worse-off.*

The function is purely additive in cases of $\gamma = 0$ and does not account for inequality, representing a Utilitarian SWF:

$$Social\ Welfare_{Utilitarian} = \sum_{i=1}^{N} w(\cdot)_i$$

[7] The Atkinson SWF requires that the wellbeing measures must be non-negative, and in instances where $\gamma \geq 1$ even strictly positive.

Greater values of $\gamma > 1$ place more weight on improving the wellbeing of those at the lower end of the distribution, even if it increases the trade-off with maximizing total wellbeing. In turn, the ability to adjust the γ parameter makes the Atkinson SWF an invaluable tool for aligning social welfare evaluations with a contextual sense of inequality-aversions and the claims-based fairness concept. As such, the degree of inequality-aversion can be adjusted to different policy areas, so that health analyses may display a different inequality-aversion than assessments of income distributions, aligning governmental evaluations of social welfare consistently with inherent preferences of their citizens[8]. In turn, the initial question regarding *whether* and to *what extent* the welfare of those worse-off should be prioritized can now be fully answered by stating: *yes, the welfare of those worse-off should be prioritized, and the inequality-aversion should be adjusted to the specific policy context in which the Atkinson SWF is applied.*

3 Subjective Wellbeing for Policy

Thus far, I have provided a justification for the prioritization of those worse-off, but I have only briefly written about the methods for measuring it. The wellbeing measure is a function $w: I \, x \, X \rightarrow R$ which assigns to each pair (i, x) consisting of an individual $i \in I$ and an outcome $x \in X$, a real number, denoted $w(\cdot)_i$ representing the wellbeing of i in x. As mentioned in the introduction, this dissertation advocates the use of subjective wellbeing as a welfare measure, specifically life satisfaction, and this chapter explores the reasons for this choice.

3.1 WELLBYs as a Measure for Social Welfare

Asking citizens about their subjective life satisfaction aligns most closely with democratic principles, respecting individual judgements and experiences. In turn, to ask how well one's life is going, aims to engage the citizen in a cognitive overall evaluation, "all-things-considered". The subjective evaluation, therefore, captures many unique behavioral phenomena such as anticipation and misprediction (Odermatt and Stutzer, 2019), adaptation to changing life circumstances (Clark et al. 2008), or relative comparisons (Luttmer, 2005; Card et al., 2012;

[8] For example, through stated preference as in (Dolan and Tsuchiya, 2011).

Perez-Truglia, 2020) which are consequently integrated into the social welfare analysis. Further, subjective wellbeing predicts voting patterns (Liberini et al. 2017; Ward, 2019) and "get-me-out-of-here" actions (Kaiser and Oswald, 2022) so that using it as a welfare measure for policy evaluations enhances the alignment of policymaking with the needs of the population and ultimately promotes a more responsive governance structure. The democratic aspect of this approach is supported by empirical evidence showing that individuals perceive life satisfaction as a major, overarching outcome of their life circumstances (Adler et al., 2017).

Crucially, life satisfaction also captures procedural elements, such as an individual's perception of how one is being treated by governmental actions (Frijters et al., 2024). As the SWF framework is inherently consequentialist, it does not directly incorporate procedural fairness but may indirectly reflect it by using citizens' cognitive evaluations of their overall life satisfaction as a welfare metric. Deontologists contend that certain actions possess intrinsic moral wrongness, independent of their outcomes, and therefore critique the SWF framework for neglecting this dimension. Nevertheless, a SWF using subjective wellbeing as a welfare measurement might accommodate an implicit pathway in which individuals who perceive themselves or others as unjustly treated will manifest this perception in their overall life evaluation, which is then subsequently incorporated into the social welfare analysis. Procedural fairness, in theory, becomes an ingredient of life satisfaction, as all wellbeing-relevant factors are integrated into the life satisfaction score, wherein the weights, relevance, and combination of these factors are implicitly determined by the individual reporting the score[9].

To apply life satisfaction for the policy analysis, this dissertation follows Frijters et al. (2020, 2024), by adopting WELLBYs as a measure for social welfare. WELLBYs display one point of life satisfaction for one person for one year where life satisfaction is measured on a 0-10 Likert scale.

[9] Although theory not always hold in practice, and measurement errors may still persist, extensive psychometric validation has been conducted and potential limitations are discussed in Chapter 5.

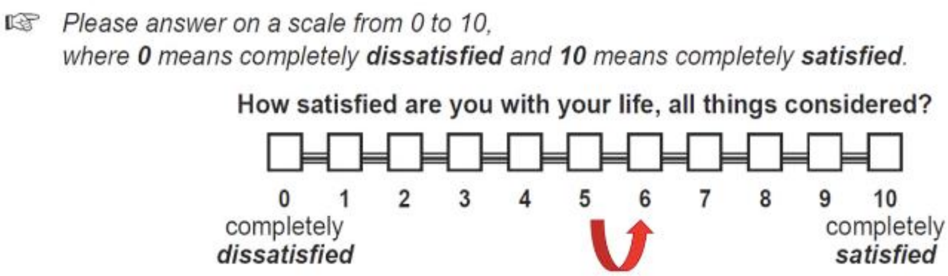

Figure 2. Source: German Socio-Economic Panel Study (GSOEP). The red arrow displays one WELLBY, as used in Frijters et al. (2024).

3.2 Intra- and Interpersonal Comparison

Not all welfare measures are suitable for application within the SWF framework, and even if life satisfaction is posited as the most suitable reflection of social welfare, its applicability within the SWF framework requires careful evaluation. Fundamentally, a welfare measure must facilitate both intra- and interpersonal comparisons of wellbeing for being a valid measurement within the SWF framework (Weymark, 2016; Adler, 2011 p. 154–236; Adler, 2019 p. 41–82; Adler and Decanq, 2022).

This necessitates the property of cardinality, implying that the difference between any two points on the 0-to-10 Likert scale is consistent across the scale. Moreover, cardinality asserts that these differences remain constant within and across individuals, as well as over time. As such, cardinality is critical for the aggregation of individual responses and is, therefore, a stringent requirement for any welfare measure intended for use within the SWF framework. While the assumption that respondents use the life satisfaction Likert scale in a cardinal manner is still a subject of ongoing research, there are three principal arguments supporting its validity.

One option aiming to prove the cardinality assumption is empirical testing. Evidence suggests high test-retest validity over two weeks, where the average absolute difference in replies is similar at all points of the scale (Krueger and Schkade, 2008). Additionally, Peasgood et al. (2018) demonstrated that respondents treated the scale in a cardinal manner when being asked to make hypothetical trade-offs between length and quality of life.

Another type of argument uses the concept of language and evolutionary processes as an underlying reasoning. Kapteyn (1997) displays a theory of preference formation which argues that to effectively communicate, it is necessary that respondents share the same understanding and use of numbers to convey information in similar ways. In turn, when individuals are asked to provide numerical responses, such as on the life satisfaction scale, they tend to treat these responses as if they were on a cardinal scale.

Ultimately, Layard and De Neve (2023) argue that using a 0-to-10 Likert scale in a purely ordinal way is implausible because respondents would need to assign each integer a distinct feeling and then allocate all variations of feelings to these points, which is impossible due to the lack of "nearness" on an ordinal scale. Thus, Layard and De Neve suggest that respondents naturally interpret these scales in a cardinal manner, treating the differences between numbers as equal increments in life satisfaction. An elaborated version of these arguments can be found in Frijters and Krekel (2021, p. 40–148). For the purposes of the following analysis, I will assume that individuals treat life satisfaction in a sufficiently cardinal manner. Potential biases stemming from the ongoing debate surrounding this assumption will be addressed in the limitations in Chapter 5.

4 Prioritarianism in Practice

4.1 The Causal Effect on Life Satisfaction due to a COVID-19 Lockdown

4.1.1 Introduction to the Policy Analysis

The COVID-19 pandemic has forced governments around the world to evaluate non-pharmaceutical interventions such as lockdowns, social distancing measures, and travel restrictions. While reducing the spread of the virus, these interventions bargain with a decrease in wellbeing of the affected population due to reductions in social activities and increases in economic burdens. This study is, to my knowledge, the first to examine the causal effect of a COVID-19 lockdown on life satisfaction, employing a difference-in-differences design to isolate the impact of the policy from the general pandemic in the context of Victoria, Australia. Moreover, I present a systematic decision procedure by constructing an Atkinson SWF to contrast the lockdown policy with a Business-as-Usual scenario, enabling future decisions about behavioral interventions to be based on causal evidence and a structured evaluation method.

Australia’s national suppression strategy involved enacting stringent lockdowns immediately upon the detection of community transmission. After a nationwide lockdown during the initial COVID-19 outbreak in March and April 2020, restrictions were eased, and the virus was largely contained through international border closures and quarantine measures. However, in July 2020, quarantine breaches led to renewed community transmission in Victoria. Due to Australia's federal structure, where each state has the authority to determine its own suppression strategies, Victoria implemented a series of stringent lockdown measures, including business shutdowns, stay-at-home directives, remote learning, and evening curfews. These interventions successfully curtailed community transmission, with daily case numbers peaking on August 5, 2020, before gradually declining, allowing for the phased easing of restrictions by late October 2020 (Bennett, 2021).

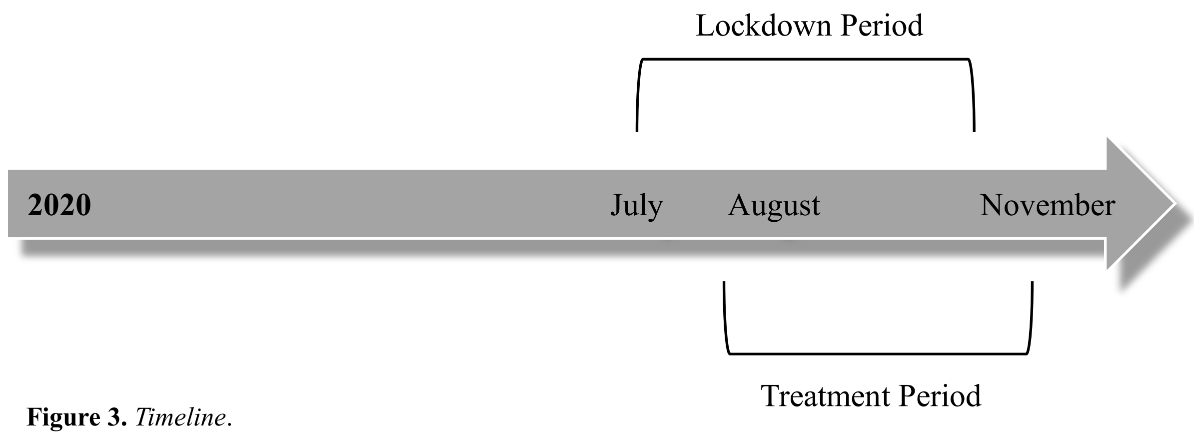

Figure 3. *Timeline*.

In turn, this study builds on the timing of data collection for the 20th wave of Australia's major household panel survey, which coincided with Victoria entering its second lockdown. This timing, combined with Australia’s federal lockdown policies, allows for the application of quasi-experimental methods, specifically a difference-in-differences design, to detach the effect of the lockdown policy from the general pandemic, whereas existing literature generally examined longitudinal evidence before, during, and after the pandemic, providing important evidence about the broader pandemic’s effects, but failing to causally isolate the policy effect. The contribution of this analysis is multifaceted. First, it provides empirical evidence on the impact of the COVID-19 lockdown on life satisfaction in an Australian context, contributing to the global discourse on pandemic responses. Second, by incorporating a Prioritarian policy analysis, the study emphasizes the ethical implications of lockdown policies and their distributional effects on different population segments. This dual focus on empirical analysis and ethical considerations aims to offer a comprehensive understanding of the lockdown's consequences, informing future public health strategies and policy decisions.

Ferranna et al. (2022) highlight that the pandemic has significantly exacerbated existing inequalities through patterns of infections, sickness, and deaths that disproportionately affect disadvantaged populations. Socioeconomic differences in healthcare access as well as the ability to invest in resources further deepen these disparities. The increase of existing inequalities through increased sickness and deaths undermines the relevance of applying Prioritarianism, particularly in evaluating the negative effects of a Business-as-Usual scenario as it would increase sicknesses compared to a lockdown. Conversely, lockdown policies might lead to a regressive distribution of its negative effects where the economic burdens and reductions in life satisfaction due to restricted activity disproportionately affect those with lower life satisfaction. An unfortunate mental health, physical health, or socioeconomic baseline status (Dolan et al., 2021) could create a more vulnerable position to economic distress and a restriction in social and recreational activities (Adler et al., 2023, Adler et al., 2020). In turn, the Prioritarian sensitivity to the distribution of policy outcomes results in a preference for policies that do not regressively affect life satisfaction. Consequently, a policy that imposes greater burdens on those with lower life satisfaction is less favorable under Prioritarianism compared to one that spreads the impacts more evenly, assuming an equal overall effect.

The subsequent analysis is structured as follows: First, the data section details the dataset, sampling methodology, and sample restrictions. The main analysis follows with a difference-in-differences approach to estimate the causal impact of the COVID-19 lockdown on life satisfaction and Propensity Score Matching is added as a robustness test. Ultimately, the difference-in-differences model is used for social welfare analysis comparing the outcomes of two distinct scenarios, Policy 1 (Lockdown) and Policy 2 (Business-as-Usual), using life satisfaction as a welfare measure and the Atkinson Social Welfare Function to incorporate a concern for those worse-off.

4.1.2 Data and Sampling Method

I analyzed data from twenty annual waves (2001–2021) of the longitudinal Household, Income and Labour Dynamics in Australia (HILDA)[10] survey, a household panel survey initiated in 2001. This survey provides a nationally representative sample of Australian households, excluding those in very remote areas and non-private dwellings. The initial wave comprised 7,682 households and subsequent annual interviews have been conducted with all household members aged 15 years or older, along with any new individuals who joined a household or turned 15 years old. In 2011, an additional 2,153 households were incorporated through a top-up sample and the survey generally exhibited low rates of sample loss, with re-interview rates rising from 87% in wave 2 to over 95% by wave 8 and remaining above that level in subsequent waves (Summerfield et al. 2021).

Data collection in 2020-2021 occurred between August and February, with over 90% of interviews completed before the end of October 2020. Prior to 2020, almost all interviews were conducted face-to-face. However, due to the pandemic, fieldwork have shifted to telephone interviews. Participants additionally completed a separate self-completion questionnaire (SCQ), including variables of interest, with a return rate averaging 90% over the analysis period. I limited the sample to respondents who provided data during 2020 and excluded respondents that lived in Victoria but were not exposed to the lockdown, therefore I excluded 87,366 observations from 16,640 individuals, leaving 236,099 observations from 16,513 individuals, with 3,796 observations from 360 individuals in the treatment group and 232,303 observations from 16,153 individuals in the control group.

Participants provided verbal informed consent for study participation, and consent from parents or guardians was obtained for household members under 18 years. The University of Melbourne's Human Research Ethics Committee granted ethics approval in 2001, which has been updated or renewed annually since (ID number 1955879).[11]

[10] Department of Social Services; Melbourne Institute of Applied Economic and Social Research, 2022, "The Household, Income and Labour Dynamics in Australia (HILDA) Survey, RESTRICTED RELEASE 21 (Waves 1-21)", https://doi.org/10.26193/24EJST, ADA Dataverse, V4)

[11] I am grateful to the Australian Government Department of Social Services for granting access to the data. No funding is provided for this analysis.

4.1.3 Quasi-Experimental Design

To estimate the causal effect of the COVID-19 lockdown on life satisfaction, this study employs a difference-in-differences design exploiting the variation in the implementation of lockdown policies across federal states in Australia. The changes in life satisfaction over time in the treatment group (Victoria, August – November 2020) are compared with changes over time in the control group (all other Australian states, August – November 2020) to isolate the policy's effect (Cunningham, 2021; De Vocht et al., 2021; Wing et al., 2018).

In defining the treatment variable, respondents in Victoria who completed the SCQ during the second half of 2020, when the lockdown was either in effect or had been lifted within the last two weeks, are identified. Specifically, the treatment group comprises of individuals who were located in a postcode in Victoria where Stage 3 mobility restrictions were implemented. This group includes all metropolitan Melbourne residents who completed the SCQ on or before November 11, 2020, and all regional Victoria residents who completed the SCQ on or before October 1, 2020. Conversely, the control group comprises of individuals who were located either in a Victorian postcode outside the lockdown period or areas outside Victoria during the same period.

The theoretical model used to isolate the policy's effect takes the following form[12]:

$$Life\ Satisfaction_{it} = \alpha + \beta_1 * Treatment_{it} + \beta_2 * Year'_t + \beta_3 * State'_{it} + \mu_i + \varepsilon_{it} \quad (1)$$

The outcome variable is the life satisfaction of respondent i interviewed in survey year t ($Life\ Satisfaction_{it}$) which is regressed on a treatment group indicator $Treatment_{it}$, dummy variables for time (vector: $Year'_t$), and dummy variables for state location (vector: $State'_{it}$). $Treatment_{it}$ equals 1 if the respondent i lived in a locked down postcode in year t, and 0 if otherwise. $Year'_t$ includes year fixed effects, leaving 2019 as the base category. $State'_{it}$ includes dummy variables for the state the individual resided in, leaving Victoria as the base category. μ_i is an individual-

[12] To prevent any confusion, the typical interaction term between *Treatment* and *Post* used to implement a difference-in-differences design is missing as the *Treatment* indicator already includes the time period of the lockdown. It is an active treatment, measuring the effect of the lockdown within the lockdown period or within two weeks afterwards. This design is consistent with other literature:
Butterworth, Peter, et al. "Effect of Lockdown on Mental Health in Australia: Evidence from a Natural Experiment Analysing a Longitudinal Probability Sample Survey." The Lancet Public Health, vol. 7, no. 5, 21 Apr. 2022, https://doi.org/10.1016/S2468-2667(22)00082-2.

specific effect that controls for individual-specific and time-invariant fixed effects in life satisfaction. ε_{it} is an error term which is assumed to be independent and identically distributed with a mean of zero and a constant variance. The coefficient of interest is β_1 which summarizes the average treatment effect of the lockdown, holding constant year, state, and individual specific characteristics.

The model is estimated using "reghdfe," an add-on to the Stata econometric package, which facilitates the inclusion of multiple levels of fixed effects while allowing for the application of survey weights. State and year fixed effects are necessary to isolate the lockdown effect, while person-specific fixed effects help to absorb residual individual variation in life satisfaction. Standard errors are adjusted for heteroskedasticity and clustered at the state level to account for potential correlations within states which is particularly important using panel data. Clustering at the state level addresses serial correlation bias, which occurs when observations within the same state are correlated over time. Failing to account for these correlations can lead to underestimated standard errors, making the treatment effects appear more significant than they are. As such, clustering aims to reflect the true variability in the data, providing more reliable estimates of the treatment effect. Furthermore, the analysis applies SCQ HILDA population weights to increase the representativeness to the Australian population by adjusting for an initial complex survey design, non-random responses, and attrition such as due to non-returns of the SCQs (Summerfield et al. 2021).

4.1.4 Parallel Trends Assumption

A difference-in-difference design allows for causal interpretation under the main assumption of parallel trends in outcomes (Cunningham, 2021; De Vocht et al., 2021). This means that in the absence of the lockdown, life satisfaction in the affected Victorian postcodes would have followed the same trajectory as in other postcodes. Testing the validity of this assumption involves plotting the mean life satisfaction scores for the treatment and control group over time to verify that they followed similar trajectories prior to the lockdown. Figure 1 demonstrates that the mean life satisfaction scores for both the treatment and control group followed a broadly similar trajectory from 2001 to 2019. While there is some divergence around 2015, overall, the trends exhibit a comparable pattern, suggesting that the parallel trends assumption is reasonably met which is necessary to warrant the credibility of the treatment and control design. Additionally, a substantial drop in life satisfaction is visible for the treatment group in 2020, reaching its lowest recorded level during the analysis period. In contrast, the control group experiences a much less pronounced decline compared to 2019, although a general decrease in life satisfaction is still observed, which is consistent with a decrease due to the broader impact of the pandemic (Bachmann et al., 2021).

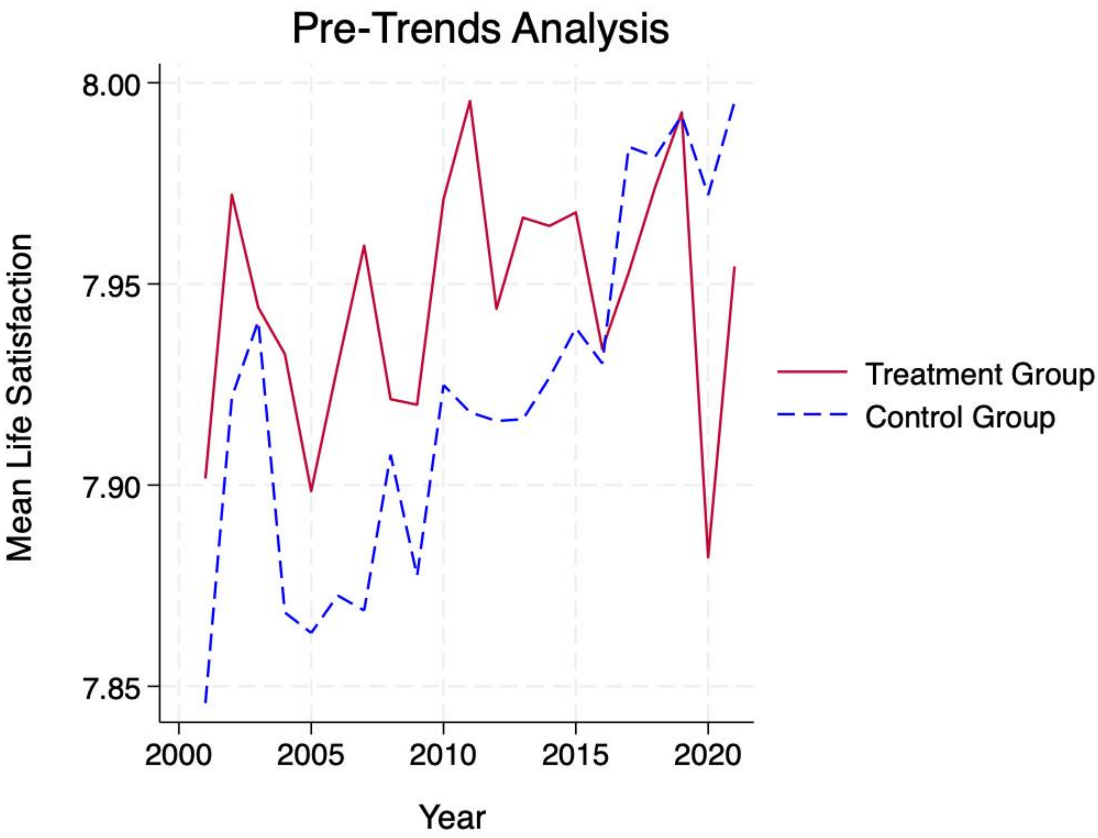

Figure 4. *Graphical Pre-Trends Analysis.*

4.1.5 Results

$$Life\ Satisfaction_{it} = \alpha + \beta_1 * Treatment_{it} + \beta_2 * Year'_t + \beta_3 * State'_{it} + \mu_i + \varepsilon_{it} \quad (1)$$

The results of Equation 1 indicate a highly significant negative treatment effect on life satisfaction due to the lockdown compared to the control group. Specifically, the difference-in-differences estimation reveals an average treatment effect of -0.03029 points (95% CI -0.0485523 to -0.012029 p = 0.006) where life satisfaction is measured on a 0-10 Likert scale.

The model is again estimated excluding individuals who reportedly have been diagnosed with COVID-19 to further isolate the policy effect from the pandemic (Equation 2). This step ensures that the estimated effect of the lockdown is not confounded by the direct health impacts of the virus itself.

$$Life\,Satisfaction_{it} = \alpha + \beta_1 * Treatment_{it} + \beta_2 * Year'_t + \beta_3 * State'_{it} + \mu_i + \varepsilon_{it} \;(2) - Sample\ restricted\ due\ to\ exlusion\ of\ individuals\ who\ have\ or\ had\ COVID-19$$

The model is estimated in the same way as in Equation 1 but excludes individuals reported to have or had COVID-19. Equation 2 delivers almost unchanged results compared to the main model, with an average treatment effect of -0.0296504 points (95% CI -0.0486519 to -0.0106489, p = 0.008).

Given the potential of the COVID-19 lockdown to disproportionately affect those with low initial life satisfaction, a stratified analysis was performed to explore this hypothesis (Equation 3). Two groups were created: Group 1 for individuals with life satisfaction below the cutoff of 4 and Group 2 for those with life satisfaction at or above the cutoff of 4. This approach aims to understand if the policy impacts were more severe for the worst-off. The cutoff of 4 is chosen based on the thresholds defined by the Office for National Statistics (Oman, 2016) for misery and has been employed by other scholars studying the worst-off such as in Dolan et al. (2021).

$$Life\,Satisfaction_{it} = \alpha + \beta_1 * Treatment_{it} + \beta_2 * Group_{it} + \beta_3 * (Treatment_{it} * Group_{it}) + \beta_4 * Year'_t + \beta_5 * State'_{it} + \mu_i + \varepsilon_{it} \;(3)$$

The coefficient of interest is β_3, which summarizes the differential treatment effect of the lockdown for the two groups, holding constant the effects of the treatment, year, state, and individual-specific characteristics. The results of Equation 3 indicate a highly significant and substantially stronger treatment effect on life satisfaction for those worst-off compared to their better-off counterparts. Specifically, the interaction term reveals an additional negative impact of -0.334 points (95% CI -0.37568 to -0.29291, p = 0.000) for those in Group 1 compared to Group 2. This contrasts with the average treatment effect observed in Equation 1, which indicates a negative impact of -0.03029 points. The coefficient for the interaction term highlights that the lockdown's adverse effects were indeed more pronounced among the worst-off, aligning with the hypothesis that restricted social and recreational activities and increased economic distress would disproportionately burden individuals with low initial life satisfaction.

Table 1 presents the summary of the just discussed results, adding information about numbers of observation, robust standard errors, and number of clusters at state level.

Variable	**Model 1: Overall Effect**	**Model 2: Excluding Covid-19 Cases**	**Model 3: Stratified Analysis**
	Coef. (robust s.e.) [95% CI]	Coef. (robust s.e) [95% CI]	Coef. (robust s.e) [95% CI]
Treatment	-0.0303 (0.0077) [-0.0486, -0.0120]***	-0.0297 (0.0080) [-0.0487, -0.0106]***	-0.0260 (0.0103) [-0.0505, -0.0013]**
Group	N / A	N / A	-4.1795 (0.0442) [-4.2841, -4.0749]***
Treatment * Group	N / A	N / A	-0.3343 (0.0175) [-0.3756, -0.2929]***
Constant	7.9022 (0.0001) [7.9019, 7.9025]***	7.9020 (0.0001) [7.9016, 7.9023]***	7.9528 (0.0006) [7.9513, 7.9544]***
Year Fixed Effects	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes
Observations	215,733	215,555	215,733
Clusters (State)	8	8	8

Note: The table summarizes three models estimating the impact of the COVID-19 lockdown on life satisfaction. Model 1 assesses the overall effect, Model 2 excludes individuals having or had COVID-19, and Model 3 differentiates between the worst-off (life satisfaction < 4) and their counterpart (life satisfaction ≥ 4). The *Treatment* indicator identifies those in locked-down postcodes. The interaction term *Treatment x Group* captures how the effect of the treatment differs for those below the cutoff of 4 compared to those above. Models include fixed effects for year, state, and individuals, with standard errors adjusted for heteroskedasticity and clustered at state level. SCQ population weights are applied for representativeness. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

4.1.6 Propensity Score Matching

The integration of Propensity Score Matching (PSM) into the quasi-experimental design enhances the comparability between treatment and control group. The difference-in-differences method controls for time-invariant differences and estimates the causal average treatment effect under the parallel-trends assumption. State and individual fixed effects address time-invariant factors, while year fixed effects account for nationwide shocks or trends (Huntington-Klein, 2021).

However, while year fixed effects control for common time-varying factors, they do not address biases from time-varying observed characteristics that may differ between the treatment and control groups. The parallel trends assumption suggests similar overall trends without treatment, but factors like changes in employment, family composition, or personality traits may evolve differently between treatment and control group. This limitation is critical as it does not account for why individuals are treated. Here, PSM adds significant value by creating a matched sample, reducing selection bias from observed characteristics, enhancing the comparison, and ideally leading to less biased estimates.

The model used to estimate the propensity scores by logistic regression incorporates a set of covariates likely to influence both the treatment assignment; living in Victoria during the treatment period, and the outcome variable; life satisfaction. These covariates include personality measures (openness, conscientiousness, extraversion, agreeableness, emotional stability, risk preferences), demographics (number of children, age, sex), and economic measures (occupation, employment).

Propensity scores were estimated by standardizing variables to account for scale differences and prevent any single covariate from disproportionately influencing the logistic regression model. Multicollinearity among covariates was evaluated through correlation analysis and variance inflation factors. The logistic model produced propensity scores for each individual, indicating the probability of lockdown exposure. Matching was performed using a nearest-neighbor approach with a caliper of 0.05, and unmatched individuals were excluded from the analysis.

Post-matching balance checks were conducted to verify the effectiveness of the matching process and confirm a balance on the chosen covariates. Figure 5 represents the standardized percent bias across covariates after matching and indicates that the covariates have achieved a balance with a bias of below the absolute value of 4%, demonstrating the success of the matching process in equating the treatment and control groups on these variables (Huntington-Klein, 2021).

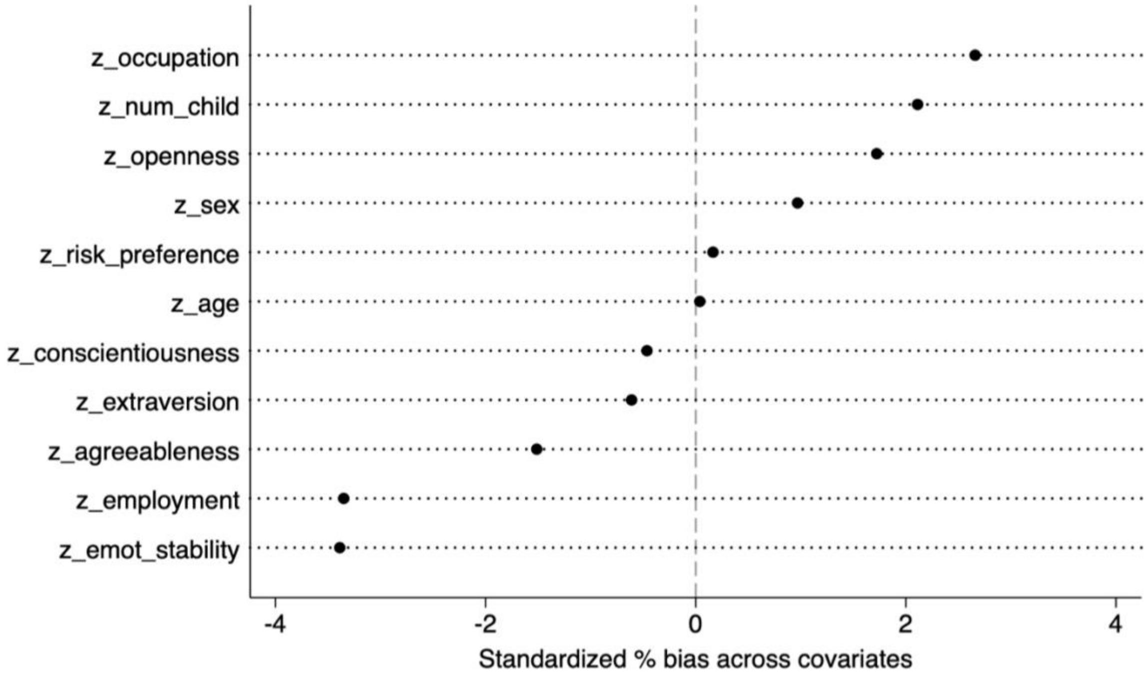

Figure 5. *Balance check after matching.*

Repeating the main analysis involved running the main model (Equation 1) with matching weights to account for the matching process. Compared to Equation 1, the results from the matched model reveal an increase in absolute magnitude despite not being significant. Displaying an effect size of -0.2987763 points (95% CI -1.25507 to 0.6575174, p = 0.48). Non-significance might occur due to the substantial reduction in observations during the matching process, ultimately reducing the observations to 1,077 for the regression model. By looking for the "perfect match" for each individual, PSM confirmed the negative direction of the policy effect even though it could not confirm its significance, prohibiting its interpretation.

Given the main concern of this dissertation regarding distribution sensitivity, additional robustness tests concerning the difference-in-differences design have been added to the appendix and will not be discussed further here. Please refer to the appendix for a Hausman test for fixed versus random effects, placebo regressions for alternative treatment years, varied time windows for the lockdown, a test for reverse causality, and stratified difference-in-differences analyses for age groups, gender, family types, and mental health baselines, as well as descriptives about the treatment and control group.

4.2 Social Welfare Analysis

After examining causality and the average treatment effect, I now direct the focus of this dissertation towards the policy analysis. Specifically, in this next step, I compare the social welfare of Victorian citizens in 2020 under two distinct scenarios: Policy 1 (Lockdown), and Policy 2 (Business-as-Usual) where the COVID-19 virus would have been treated like a regular flu[13]. Wellbeing is assessed using life satisfaction as a welfare measure, and the wellbeing numbers are transformed using the Atkinson SWF. Following the decision criteria of Prioritarian SWFs, the totals of the Atkinson-transformed WELLBYs for each scenario are compared to rank the social welfare per policy outcome.

4.2.1 Policy 1 Lockdown

To display the construction of the scenarios, I begin explaining the lockdown scenario using the main model (Equation 1). As proposed in Adler (2019, p. 161–202), the model was used to predict the life satisfaction scores for a population living in the lockdown scenario based on the difference-in-differences design explained above. The predicted data is preferred over observational data as it includes the isolated estimate of the specific causal effect of the lockdown on life satisfaction. The model predicts life satisfaction for each individual based on the treatment effect, year, and state fixed effects, as well as individual-specific fixed effects and an error term. These fixed effects control for variables that are constant over time but may vary across individuals or states, ensuring that the estimated treatment effect is isolated from other influences, thus providing a more accurate prediction of the causal impact of the lockdown on life satisfaction.

$$\begin{aligned}&\widehat{Life\ Satisfaction}_{it\ (Lockdown)}\\&\quad = \alpha + \beta_1 * Treatment_{it} + \beta_2 * Year'_t + \beta_3 * State'_{it} + \mu_i + \varepsilon_{it}\end{aligned}$$

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[13] This advice was given shortly before the COVID-19 pandemic by the WHO (2019), advising that once a virus like COVID-19 becomes widespread, the costs of containment and eradication outweigh the benefits, as it is unlikely to be contained indefinitely.

Following this, I scaled the predicted sample data to represent the entire population of Victoria using the SCQ survey weights, and subsequently transformed it using the Atkinson SWF. This transformation applied a strictly concave and increasing function to prioritize the life satisfaction of the least well-off individuals. I adopted a moderate concern for those worse-off using an inequality aversion parameter of $\gamma = 1$. This reduces the Atkinson SWF to the natural logarithm and ensures a moderate trade-off between efficiency and equality as mentioned in Chapter 2. Assuming that the life satisfaction scores remain constant for a year, consistent with the applications in Frijters and Krekel (2021, p. 333–424), the transformed total represents the social welfare of Victoria for 2020 under the predicted and scaled outcome of the lockdown policy.

$$Social\ Welfare_{Lockdown} = \sum_{i=1}^{N} ln(LS_i) = \mathbf{13.775.625}\ Prioritarian\ WELLBYs$$

4.2.2 Policy 2 Business-as-Usual

To construct the Business-as-Usual scenario I am exploiting the 2020 control group. Using the control group instead of predicting the life satisfaction data for Victoria based on 2001-2019 crucially includes the broader effects of the pandemic.

Further evaluating the Business-as-Usual scenario involves estimating the fatality rates in case of a mass exposure to the virus before vaccinations are developed and distributed. Conservatively assuming that the entire population of Victoria will get in contact with the virus and applying a total mortality rate of 0.67%, as suggested in Ferranna et al. (2022), to the 6.68 million citizens of Victoria results in an estimated 44,756 additional deaths due to the missing lockdown. These additional deaths represent lost WELLBYs, which need to be subtracted from the social welfare in 2020.

Moreover, these deaths disproportionately affect individuals with low income, poor health, and older age, which impacts the distribution of welfare (Ferranna et al., 2022). To integrate these deaths into the distribution, I first scaled the life satisfaction scores using survey weights to represent the population of Victoria. Then, I created a mortality probability score based on income, health, and age, as proposed in Ferranna et al. (2022). This probability score was used to assign the 44,756 additional deaths, reflecting the likelihood of individuals dying due to the virus. Individuals who are older, have lower income, or suffer from long-term health issues are more likely to die due to the virus. After assigning the deaths, I adjusted the scaled distribution by removing the life satisfaction values of those marked as deceased. The scores were then transformed using the Atkinson SWF and aggregated to represent the social welfare of Victoria considering the additional deaths indirectly in a distributional manner.

To directly account for the saved lives due to the lockdown, I deducted the WELLBYs that would have been lost due to the additional deaths in a Business-as-Usual scenario. To calculate these lost WELLBYs, I used the transformed life satisfaction scores of the respondents marked as deceased and adjusted their score with the indifference point, as proposed by Frijters and Krekel (2021, p. 40-128), which deducts the life satisfaction point of a person being indifferent between death and alive. The current best estimate for the equivalent life satisfaction of death is a level of 2, which is derived in Peasgood et al. (2018). Next, I multiplied this by a remaining lifetime of 6 years which is derived in Layard et al. (2020), and in Ferguson et al. (2020), and similar to the one used in Dolan's and Jenkis' (2020) analysis about the monetary value of deaths prevented from COVID-19 lockdowns. I then aggregated the lost WELLBYs for all 44,756 deceased individuals to reflect the additional deaths that would have occurred without the lockdown in Victoria.

Consequently, the social welfare in Victoria for 2020 under a Business-as-Usual scenario (Equation 7) displays as the distributionally adjusted and transformed sum of life satisfaction scores minus the transformed lost WELLBYs due to the additional deaths. Specifically, LS_i is the life satisfaction score for individual i, $LS_{j,deceased}$ is the life satisfaction score for the deceased individual j, D is the total number of additional deaths, and Y is the remaining lifetime of the deceased in years, corrected by the indifference point I.

$$\begin{aligned} Social\ Welfare_{Business-as-Usual} \\ &= \sum_{i=1}^{N-D} ln(LS_i) \\ &- \sum_{j=1}^{D} (ln(LS_{j,deceased} - I_{j,deceased}) * Y_{j,deceased}) \\ &= \mathbf{52.366.212}\ Prioritarian\ WELLBYs \end{aligned}$$

4.2.3 Social Welfare Comparison

The Prioritarian comparison of social welfare between the two scenarios leads to a clear conclusion: the analysis reveals that the lockdown policy is not preferable. The reduction in life satisfaction due to decreased social interaction and heightened economic distress during the lockdown significantly outweighs the wellbeing loss from additional deaths that would have occurred without lockdown measures.

5 Discussion

5.1 Conclusion

In conclusion, focusing solely on total welfare neglects crucial concerns of fairness. In turn, behavioral economics highlights that citizens value fairness and display an inequality-aversion, supporting the need to prioritize the welfare of those worse-off, even at the cost of efficiency. SWFs adhering to the Pigou-Dalton Axiom, such as Prioritarian and Egalitarian SWFs, are therefore preferable, with the Prioritarian Atkinson SWF being particularly valuable for its emphasis on absolute wellbeing and its flexibility in addressing inequality.

Following Frijters et al. (2020, 2024), I argued that using subjective life satisfaction as a welfare measure aligns with democratic principles by respecting individual judgments and experiences, thus enhancing policy responsiveness. Life satisfaction predicts key behaviors like voting and includes perceptions of procedural fairness, which are consequently incorporated into the welfare analyses. Despite debates over the cardinal interpretation of life satisfaction scores, strong arguments support its validity, making it a suitable measure for SWFs.

Building on this theoretical foundation, I analyzed the impact of a COVID-19 lockdown on life satisfaction applying a difference-in-differences approach. The results revealed a highly significant negative effect, particularly strong for those with initial low life satisfaction, indicating the lockdown's regressive impact. Ultimately, comparing the lockdown to a Business-as-Usual scenario using an Atkinson SWF suggests that the Business-as-Usual approach is preferable, as it yields higher overall wellbeing.

5.2 Policy Implications

The policy implications of this dissertation are twofold. First, I provided a motivation and a guidance for how to prioritize those worse-off in practice which may induce a shift in how policy analysts evaluate governmental actions. Second, I provided empirical evidence on the impact of a COVID-19 lockdown on life satisfaction in an Australian context and constructed a Prioritarian policy analysis which informs future behavioral interventions.

5.2.1 Motivating an Ethical Shift in Current Evaluation Methods

Policy evaluations have been dominated by Utilitarianism, focusing on maximizing total welfare while neglecting fairness and inequality-aversion. This dissertation advocates for Prioritarianism, demonstrating how an Atkinson SWF can be constructed for policy analyses using subjective wellbeing as a welfare measure. I provided both, a rationale, and a guide for applying Prioritarianism using WELLBYs, offering a concise framework for incorporating inequality-aversion into future policy analyses. Consequently, this approach could significantly impact public policy by encouraging analysts to promote policies that impose less regressive burdens.

Furthermore, governments relying on subjective wellbeing data, typically employ Cost-Benefit Analyses (CBAs) for policy evaluations, which can be seen as a form of Utilitarian SWFs[14] where wellbeing is measured by Monetary Equivalences (MEs). However, CBAs are further criticized for favoring the rich, assigning a monetary value to non-monetary benefits based on financial resources and preferences, and therefore, often overvaluing the preferences of wealthier individuals while neglecting the diminishing marginal utility of income (Adler & Posner, 1999; Adler & Posner, 2009). A shift from Utilitarian CBAs to Prioritarian SWFs would ensure that not only those worse-off in terms of income are no longer neglected, but also those disadvantaged according to the applied welfare measure are given priority. Nevertheless, CBAs often remain a more straightforward tool for evaluating whether a policy or action resulted in a net welfare gain. Policy analysts who continue to rely on CBAs may consider adopting complementary approaches such as Distributional Cost-Effectiveness Analysis (DCEA) (Cookson et al., 2021). DCEA allows for the incorporation of Prioritarian approaches and other

[14] Another interpretation, following Adler, would be to see CBAs as an alternative policy evaluation tool as it does not require interpersonal comparisons.

methods of evaluating distributions, offering a way to address equity concerns that traditional CBA might overlook, without the necessity of constructing a SWF.

5.2.2 Informing Future Behavioral Interventions

In 2020, life satisfaction in Victoria reached its lowest level in two decades. Although disentangling the effects of the lockdown policy from those of the pandemic is challenging, particularly due to potential interaction effects, the results indicate that the lockdown policy significantly decreased the wellbeing of Victorian citizens.

The most pronounced result is the regressive distribution of the lockdown effects, where the reduction in life satisfaction disproportionately affects those worse-off in terms of life satisfaction. Consistent with these results, further stratified analysis (Table 9, Appendix), based on Mental Health Index categories, reveals that respondents with low initial mental health (scores ≤ 33) experienced the most substantial negative impact from the policy (-0.4190*), indicating that this group was particularly vulnerable. Moreover, the decline in life satisfaction appears to be primarily driven by the youngest age group, 15-19 years old (Table 6, Appendix), where the policy effect is significantly negative (-0.0954**), indicating a substantial decrease in life satisfaction. Furthermore, men appear to have been substantially more affected by the lockdown than women (Table 7, Appendix). For males, the policy is associated with a significant negative impact on life satisfaction (-0.0806*). In contrast, the treatment effect for females is positive (0.0273) but not statistically significant.

These empirical findings are critical for informing future behavioral interventions. Individuals with lower life satisfaction and poor mental health are disproportionately affected. If future lockdowns are necessary, they should be accompanied by targeted mental health interventions, designed by health professionals and psychologists, potentially including digital tools like mindfulness apps or virtual meetings. The significant impact on men also warrants specific consideration in these strategies.

If public policy neglects to address declines in wellbeing caused by its actions, citizens may express their dissatisfaction by voting against the incumbent government. Ward (2019) shows that subjective wellbeing significantly predicts electoral success for incumbents, suggesting that governments can improve their re-election prospects by prioritizing policies that enhance public wellbeing.

In turn, the social welfare analysis indicates that the lockdown may not have been the optimal decision. The social welfare outcomes in the Business-As-Usual scenario significantly surpass those under the lockdown, aligning with earlier predictive models comparing these two scenarios (Frijters 2020a, 2020b; Layard et al., 2020)[15].

5.3 Limitations

5.3.1 Limitations of Social Welfare Functions

While discussing the differences between Utilitarianism, Prioritarianism, and Egalitarianism in Chapter 2, I have not addressed the rationale for choosing the SWF framework itself or the limitations that come with it. The SWF framework is a normative decision-making tool that posits one outcome as morally superior to another if it results in greater overall wellbeing. As such, this approach is based on two controversial assumptions[16]: Welfarism, which holds that wellbeing is the only metric that ultimately matters, and Consequentialism, which asserts that the morality of an action is determined solely by its outcomes.

Amartya Sen (1979) critiques Welfarism for its narrow focus on individual wellbeing, excluding other morally relevant factors like justice, rights, and the sources of wellbeing. He argues that this *informational constraint* is overly restrictive, neglecting essential aspects of moral reasoning. For instance, Welfarism fails to address situations where wellbeing is derived from morally questionable actions such as torture. Similar critiques apply to Consequentialism, which is often in contrast with Deontology asserting that certain actions are inherently wrong regardless of their outcomes, criticizing the SWF for neglecting additional information such as an intrinsic moral significance of actions, irrespective of consequences.

[15] Frijters (2020a): https://clubtroppo.com.au/2020/03/21/the-corona-dilemma/; Frijters (2020b): https://clubtroppo.com.au/2020/04/08/how-many-wellbys-is-the-corona-panic-costing/; Layard et al. (2020): http://cep.lse.ac.uk/pubs/download/occasional/op049.pdf.

[16] As I introduced CBAs in the preceding Chapter, I would like to mention that CBAs are similarly grounded in Welfare Consequentialism and are subject to comparable, if not more extensive, critiques.

As proposed in Chapter 3, this issue may be mitigated by using subjective wellbeing as a measure of welfare. Empirical evidence indicates that people tend to exhibit a preference for distributional justice (Skedgel et al., 2014). If governments were to implement policies that are intuitively morally wrong and unjust, and if citizens express an inherent preference for justice, then, in theory, their life satisfaction would likely decrease which would result in a negative evaluation of the implemented policies.

5.3.1 Limitations of Prioritarianism

Prioritarianism, although offering a compelling ethical framework for prioritizing those worse-off, faces significant limitations, particularly in its focus on absolute rather than comparative justice. This focus results in two key critiques: First, its failure to distinguish adequately between intra- and interpersonal cases, and second, its insensitivity to the magnitude of benefits when comparing across individuals.

Otsuka and Voorhoeve (2009) offer a critical examination of these limitations. First, Prioritarianism is critiqued for treating benefits the equally in cases involving multiple individuals. This approach fails to account for the moral significance of the *Separateness of Persons,* a concept central to justice theories which asserts that each individual's situation should be considered individually, so that their relative wellbeing compared to others should be incorporated in moral reasoning. Unlike Prioritarianism, Egalitarianism explicitly addresses the *Separateness of Persons* by focusing on the comparative wellbeing of individuals, emphasizing an intrinsic importance of reducing inequalities between them.

The second critique further underscores this limitation by highlighting Prioritarianism's insensitivity to the magnitude of benefits across individuals. Prioritarianism tends to prioritize helping those who are worse-off, even if the benefit they receive is relatively small compared to a much larger benefit that could be provided to someone who is better-off. This can lead to morally counterintuitive outcomes where very small gains for those worse-off are prioritized over significant gains for others. Again, this critique points to the problem of Prioritarianism's focus on absolute wellbeing rather than making comparative judgments about how much benefit each person would receive.

One way to address the limitations of Prioritarianism, particularly its insensitivity to the magnitude of benefits across individuals, is by using thought experiments that help calibrate ethical intuitions regarding inequality-aversions (Otsuka & Voorhoeve, 2009). Alternatively, stated preference methods, such as those employed by Dolan and Tsuchiya (2011), can be utilized to estimate the level of inequality-aversion that a society deems acceptable, aligning policy decision with democratic values.

5.3.2 Limitations of Life Satisfaction as a Measure for Social Welfare

Even though I advocate for the incorporation of life satisfaction into policy analyses, it is essential to acknowledge its inherent limitations. Fundamentally, I propose the adoption of the theory of Contextualism (Alexandrova, 2017, pp. 132-133), which posits that the semantic content of wellbeing is variable and that wellbeing measures should be contextually tailored to the specific group of individuals and the circumstances under consideration. This perspective suggests that life satisfaction may not always serve as the most suitable measure of wellbeing; rather, it should be employed when the context warrants its application.

Krekel and MacKerron (2023) emphasize that using life satisfaction as a metric requires a large number of observations for precise policy impact estimates, limiting its effectiveness for smaller interventions or those targeting limited populations. Additionally, life satisfaction is less suitable for assessing short-term or one-off interventions, such as infrequent museum visits or sporadic traffic delays. In these cases, experiential valuation, which captures real-time hedonic experiences, may be more appropriate. However, life satisfaction is particularly valuable for evaluating large, complex policy initiatives such as lockdowns, as it integrates multiple life-domains into a single measure (Frijters et al., 2024).

Regardless of its contextual applicability, the cardinality assumption in life satisfaction measures remains a subject of ongoing research and may present a significant limitation, particularly for Prioritarianism within the SWF framework. The SWF might misinterpret disparities if life satisfaction scores do not accurately reflect changes in wellbeing, potentially leading to policy recommendations that misalign with the true distribution of wellbeing and result in overvaluing minor improvements for those worse-off while undervaluing significant gains for those better-off.

5.3.3 Limitations of the Policy Analysis

While the policy analysis provides vital insights into lockdowns' impact on life satisfaction, five methodological limitations must be considered. First, the quasi-experimental design leaves the true counterfactual uncertain. Without a lockdown in Victoria, higher infection rates could have negatively impacted life satisfaction more severely, complicating the causal interpretation. Although efforts were made to account for increased infections in the Business-as-Usual scenario, the true counterfactual impact on life satisfaction remains unknown.

Second, the context-specific nature of this study limits the broader applicability of the findings. The unique social, economic, and cultural conditions in Australia, along with other contextual factors such as public and media perceptions of COVID-19, may not fully translate to other populations.

Third, the reliance on a single measurement of life satisfaction during the lockdown period restricts the analysis to short-term effects, limiting the capacity to evaluate the duration or persistence of these changes. To reduce this limitation, an additional analysis was conducted, as detailed in the appendix, which varied the time periods surrounding the lockdown (Table 4). The results indicate that extending the observation period tends to amplify the negative effects on life satisfaction, with the most pronounced declines observed when the entire year of 2020 is considered.

Furthermore, potential biases from non-random sample attrition and response rates pose limitations, even with survey weighting adjustments. These may not fully correct for under-representation of groups like recent immigrants or those in non-private housings. Techniques such as Inverse Probability Weighting or Multiple Imputation could mitigate these biases by adjusting for response likelihood and accounting for missing data, improving external validity.

Finally, the assumptions underlying the policy evaluation are highly sensitive, warranting analyses to assess their impact on outcomes. Parameters such as the remaining years of life and the mortality scores heavily influence the outcomes. Therefore, the disparity in social welfare between the lockdown and Business-as-Usual scenarios should be viewed as indicative rather than definitive, offering a directional policy recommendation.

5.4 Further Research

To address a contextual bias, the policy’s effect should be compared with causal effects observed in other countries. Given that this study is the first to isolate the impact on life satisfaction, further research should expand on this. For example, regression discontinuity designs could be applied in countries like Germany, where COVID-19 policies were index-based. The “incidence-number” could serve as a running variable, with case data available from the Robert Koch-Institute and life satisfaction measures from the German Socio-Economic Panel (GSOEP) in 2020.

Furthermore, future studies could examine the role of procedural fairness in mediating subjective wellbeing within the SWF framework. Although not directly accounted for in the SWF, perceptions of fairness may influence life satisfaction scores, which are integral to social welfare analysis. This could be explored by analyzing the impact of perceptions of government actions on life satisfaction within the SWF framework. Additionally, the influence of public and media perceptions of COVID-19 warrants investigation, particularly in how information dissemination affects life satisfaction and how communication strategies could mitigate psychological impacts during pandemics.

Ultimately, developing more sophisticated models to simulate counterfactual scenarios, including variations in public health responses could enhance understanding of lockdowns' causal impacts on life satisfaction. Incorporating an uncertainty module, as suggested by Adler (2019, pp. 161-202), would enable the assessment of how varying parameters influence policy outcomes, resulting in a more nuanced and robust policy analysis.

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Appendix

Table 2. *Hausman Test for Fixed Effects versus Random Effects.*

Coefficient	Fixed Effects (b)	Random Effects (B)	Difference (b – B)	Std. Error
Treatment	-0.0019836	0.0050077	-0.0069913	0.00174

Test Statistic	Chi2(1)	p-value
Hausman Test	16.14	0.0001

A Hausman test was conducted to compare the fixed effects and random effects models in order to determine the appropriate model for the panel data. The results, presented in Table 2, indicate that the p-value (0.0001) is below the significance level of 0.05, leading to the rejection of the null hypothesis that the differences in coefficients are not systematic. This suggests that the fixed effects model is preferred over the random effects model, as it provides more consistent estimates in the presence of potential systematic differences between the models.

Table 3. *Placebo Regressions for different Treatment Years.*

Variables	(1) 2011	(2) 2013	(3) 2015	(4) 2017
placebo_treatment_2011	0.0400**			
	(0.0121)			
placebo_treatment_2013		0.0093		
		(0.0129)		
placebo_treatment_2015			0.0108	
			(0.0084)	
placebo_treatment_2017				-0.0212
				(0.0151)
Constant	7.901***	7.901***	7.902***	7.902***
	(0.0002)	(0.0002)	(0.0001)	(0.0002)
Observations	214,904	214,901	215,699	215,707
R-squared	0.554	0.554	0.554	0.554

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

Table 3 presents the results of placebo regressions for the randomly chosen years 2011, 2013, 2015, and 2017, where the treatment periods were artificially set before the actual treatment period. The results show that the placebo treatments in 2013, 2015, and 2017 have no statistically significant effect on life satisfaction. However, the placebo treatment in 2011 shows a statistically significant positive effect on life satisfaction, which suggests that there may have been external factors or confounding variables affecting the outcome during that year. Overall, the results support the notion that the lockdown is isolated to the 2020 treatment period.

Table 4. *Alternative Treatment Period lengths.*

Variables	(1) Lockdown	(2) Lockdown + 2	(3) Lockdown + 4	(4) Lockdown + 8	(5) Whole 2020
Treatment_lockdown	-0.0156				
	(0.0142)				
Treatment_plus2		-0.0303***			
		(0.0077)			
Treatment_plus4			-0.0279**		
			(0.0109)		
Treatment_plus8				-0.0397***	
				(0.0081)	
Treatment_2020					-0.0834***
					(0.0061)
Constant	7.902***	7.902***	7.902***	7.902***	7.903***
	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Observations	215,733	215,733	215,733	215,733	215,733
R-squared	0.554	0.554	0.554	0.554	0.554

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

Table 4 presents the results of the regression analysis assessing the impact on life satisfaction when varying the defined period around the lockdown. The analysis explores five scenarios: the original lockdown period, the period extended by 2 weeks, 4 weeks, and 8 weeks, as well as the entire year of 2020. The estimated effect on life satisfaction is negative but not statistically significant (-0.0156) in the case of the exact lockdown period, suggesting that this initial period may not have had a substantial impact on life satisfaction. When the defined period is extended by 2 weeks beyond the lockdown, which is the scenario used in the main analysis, the results show a statistically significant negative effect on life satisfaction (-0.0303). Extending the period by 4 weeks also yields a significant negative effect (-0.0279), albeit slightly smaller in magnitude. When the period is extended by 8 weeks, the negative impact becomes even more pronounced (-0.0397) and remains highly significant. Finally, when the entire year 2020 is considered, the effect is markedly negative and statistically significant (-0.0834), reflecting the considerable cumulative impact of the year as a whole. These findings suggest that extending the defined period around the lockdown tends to reveal a stronger negative effect on life satisfaction, with the most pronounced decline observed when the entire year 2020 is included.

Table 5. *Test for Reverse Causality.*

Variables	(1) Treatment
Life Satisfaction	-0.0004
	(0.0002)
Constant	0.0194***
	(0.0017)
Observations	215,733
R-squared	0.322

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

Table 5 presents the results of a test for reverse causality, where life satisfaction is used as the independent variable to predict the likelihood of being in the treatment group. The purpose of this test is to assess whether life satisfaction could be driving the assignment to the treatment group, rather than the other way around. The coefficient for life satisfaction is -0.0004, and it is not statistically significant. This suggests that life satisfaction does not have a significant impact on whether an individual is classified as being in the treatment group.

Table 6. *Difference-in-Differences Effect per Age Group.*

Variables	(1) 15-19	(2) 20-29	(3) 30-54	(4) 55-69	(5) 70+
Treatment	-0.0954**	0.0578***	0.0142	0.0029	-0.0053
	(0.0376)	(0.0140)	(0.0198)	(0.0282)	(0.0292)
Constant	8.245***	7.862***	7.715***	8.027***	8.336***
	(0.0007)	(0.0002)	(0.0003)	(0.0005)	(0.0009)
Observations	15,858	35,167	96,216	46,761	19,825
R-squared	0.644	0.613	0.582	0.634	0.599

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

The results presented in Table 6 suggest that the overall negative effect of the treatment on life satisfaction observed in the main analysis is primarily driven by the youngest age group, 15-19 years old. In this age group, the treatment effect is significantly negative (-0.0954), indicating a substantial decrease in life satisfaction. This effect is notably larger than the effects observed in other age groups, where the impact is either positive (as seen in the 20-29 age group) or negligible and statistically insignificant (as seen in the 30-54, 55-69, and 70+ age groups). These findings imply that the overall negative impact detected in the broader population is likely influenced by the particularly strong adverse effects experienced by the youngest cohort. This suggests that individuals in the 15-19 age range were particularly vulnerable to the negative consequences of the treatment, which may reflect unique challenges faced by this age group during the lockdown period such as school closures. Interestingly, the second youngest age group 20-29 seems to have increased in life satisfaction due to the lockdown.

Table 7. *Difference-in-Differences Effect per Gender.*

Variables	(1) Male	(2) Female
Treatment	-0.0806*	0.0273
	(0.0410)	(0.0351)
Constant	7.890***	7.913***
	(0.0007)	(0.0006)
Observations	98,719	117,231
R-squared	0.566	0.543

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

The results in Table 7 highlight the differential impact of the treatment on life satisfaction by gender. For males, the treatment is associated with a negative effect on life satisfaction (-0.0806), which is statistically significant at the 10% level, thus, suggests that men experienced a substantial decline in life satisfaction as a result of the lockdown. In contrast, for females, the treatment effect is positive (0.0273) but not statistically significant. These findings suggest that the overall negative effect of the treatment, as observed in the broader analysis, may be driven primarily by the male population.

Table 8. *Difference-in-Differences Effect per selected Family Type.*

Variables	(1) Couple without children	(2) Couple with children < 15	(3) Lone parent with children < 15	(4) Lone person
Treatment	-0.0039	-0.0096	0.2030**	-0.0116
	(0.0161)	(0.0169)	(0.0678)	(0.0268)
Constant	8.197***	7.945***	7.298***	7.587***
	(0.0003)	(0.0003)	(0.0007)	(0.0005)
Observations	64,836	58,343	7,094	31,022
R-squared	0.601	0.588	0.582	0.601

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

Table 8 presents the difference-in-differences estimates of the treatment effect on life satisfaction across chosen family types. The results show that the treatment had little to no significant impact on life satisfaction for couples without children, couples with children under 15, and individuals living alone. However, lone parents with children under 15 experienced a significant positive effect on life satisfaction (0.2030), suggesting that this group may have benefited from the lockdown.

Table 9. *Difference-in-Differences Effect per Mental Health Categories.*

Variables	(1) Low Mental Health	(2) Medium Mental Health	(3) High Mental Health
Treatment	-0.4190*	0.0534	0.0078
	(0.2020)	(0.0357)	(0.0127)
Constant	5.629***	7.188***	8.258***
	(0.0046)	(0.0007)	(0.0002)
Observations	5,203	51,795	152,692
R-squared	0.588	0.527	0.544

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

Table 9 presents the Difference-in-Differences estimates of the treatment effect on life satisfaction across three mental health categories: low, medium, and high. These categories are defined based on the Mental Health Index with low mental health (scores ≤ 33), medium mental health (34 - 66), and high mental health (scores > 66). The results show that individuals with low mental health experienced a significant and substantial negative impact from the treatment (-0.4190), suggesting that this group was particularly vulnerable to the negative effects. In contrast, the treatment effects for individuals with medium (0.0534) and high (0.0078) mental health were not statistically significant, indicating little to no impact on life satisfaction for these groups. This is consistent with the hypothesis that the lockdown might have affected those worse-off more strongly, as argued in Chapter 4.

Table 10. *Descriptives for Treatment vs Control group.*

Variable	Treatment Group Mean (s.d)	Control Group Mean (s.d)
Age	45.327 (18.731)	44.071 (17.631)
Sex	1.535 (0.499)	1.537 (0.499)
Income	51,230.348 (46,840.472)	42,775.369 (42,416.782)
Agreeableness	4.242 (3.838)	4.393 (3.586)
Conscientiousness	3.963 (3.782)	4.160 (3.542)
Openness	3.129 (3.543)	3.220 (3.304)
Emotional Stability	4.082 (3.838)	4.305 (3.600)
Extraversion	3.309 (3.598)	3.436 (3.347)
Risk preference	3.725 (4.056)	3.522 (3.922)
Mental Health Index	64.795 (26.183)	66.997 (27.748)
Long-Term Health	1.736 (0.447)	1.738 (0.440)
Have/had COVID-19	1.997 (0.054)	1.990 (0.100)

The treatment and control groups appear well-balanced across the chosen covariates, with mean values and standard deviations being similar between the two groups. This suggests no substantial differences between the groups in terms of age, sex, personality traits, risk preference, mental and long-term health, and in having or have had COVID-19. However, income seems to be different between Victoria (Treatment) and other states (Control).

Do-Files

/////// This file is used for the Main Model, Robustness Tests, and further stratified analyses:

```
clear all
use


****************** Prepare Treatment Design
* Interview date
generate intdatescq = date(SCQ_complete, "DMY")
gen intdate2=intdate
format intdate2 %td
gen int_month=month(intdate2)
gen int_day=day(intdate2)
gen int_yr=year(intdate2)
generate numdate = date(PQ_complete, "DMY")
gen intdate_dv=intdatescq
replace intdate_dv=numdate if intdatescq<0 & intdatescq<.
replace intdate_dv=numdate if intdatescq==.

* Gen active_treatment and notreatvic20
gen treatment_reg=(intdate_dv>=22103 & intdate_dv<=22189)
gen treatment_metro=(intdate_dv>=22103 & intdate_dv<=22230)
gen active_treatment=1 if treatment_reg==1 & capital_area==29
replace active_treatment=1 if treatment_metro==1 & capital_area==21
replace active_treatment=0 if active_treatment==.
gen notreatvic20=(active_treatment==0 & wave==20 & state==2)


*************************** Main Model, Equation 1 and 2
* Main Model with FE, weights and state level clustered s.e.
reghdfe life_satisfaction active_treatment [pweight=cws], absorb(pid wave state)
cluster(state)
estimate store main

* Dropping those who had covid in 2020
reghdfe life_satisfaction active_treatment [pweight=cws] if covid_ever!=1, absorb(pid wave
state) cluster(state)
estimate store droppedcovid

*************************** Stratified Analysis
gen group1 = 0

* Define intervals below/above median
replace group1 = 1 if life_satisfaction < 4

* Regression with Dummy for Group
```

```
reghdfe life_satisfaction group1##active_treatment [pweight=cws], absorb(pid wave state)
cluster(state)

************************************************************************
************************************************************************
***************************************************************
Robustness Checks
************************************************************************
************************************************************************
***************************************************************

*************************** Parallel Trends Figure 4

* Identify the treatment group (Victoria)
gen treated= (state==2) &!missing(state)

* Calculate mean life satisfaction by year and treatment group
collapse (mean) life_satisfaction, by(year treated)

* Plot the trends
twoway (line life_satisfaction year if treated == 1, lcolor(red) lpattern(solid) lwidth(medium))
///
    (line life_satisfaction year if treated == 0, lcolor(blue) lpattern(dash) lwidth(medium))
    legend(order(1 "Treatment Group" 2 "Control
    yscale(range(6 10))

*************************** Hausman Test for Random vs Fixed Effects Table 2

* Set panel structure
xtset pid wave

* Run Fixed Effects Model without clustering
xtreg life_satisfaction active_treatment if notreatvic20 == 0, fe
estimates store fe_model

* Run Random Effects Model without clustering
xtreg life_satisfaction active_treatment if notreatvic20 == 0, re
estimates store re_model

* Perform the Hausman Test -> shows that FE is more apprioriate
hausman fe_model re_model, sigmamore
outreg2 using hausman_results.doc, replace ctitle(Test 2014)


*************************** Placebo Regressions for other Years Table 3

* Define placebo treatment periods for 2011
gen placebo_treatment_reg_2011 = (intdate_dv >= 18636 & intdate_dv <= 18822) //
Equivalent to 06/08/2011 - 17/09/2011
gen placebo_treatment_metro_2011 = (intdate_dv >= 18508 & intdate_dv <= 18958) //
Equivalent to 09/07/2011 - 28/10/2011
```

```
gen placebo_active_treatment_2011 = 1 if placebo_treatment_reg_2011 == 1 & capital_area
== 29
replace placebo_active_treatment_2011 = 1 if placebo_treatment_metro_2011 == 1 &
capital_area == 21
replace placebo_active_treatment_2011 = 0 if placebo_active_treatment_2011 == .

gen notreatvic11 = (placebo_active_treatment_2011 == 0 & wave == 11 & state == 2)
reghdfe life_satisfaction placebo_active_treatment_2011 [pweight=cws] if notreatvic11 == 0,
absorb(pid wave state) cluster(state)
outreg2 using Placebo_Tests.doc, replace ctitle(2011)

* Define placebo treatment periods for 2013
gen placebo_treatment_reg_2013 = (intdate_dv >= 19380 & intdate_dv <= 19566) //
Equivalent to 06/08/2013 - 17/09/2013
gen placebo_treatment_metro_2013 = (intdate_dv >= 19252 & intdate_dv <= 19702) //
Equivalent to 09/07/2013 - 28/10/2013

gen placebo_active_treatment_2013 = 1 if placebo_treatment_reg_2013 == 1 & capital_area
== 29
replace placebo_active_treatment_2013 = 1 if placebo_treatment_metro_2013 == 1 &
capital_area == 21
replace placebo_active_treatment_2013 = 0 if placebo_active_treatment_2013 == .

gen notreatvic13 = (placebo_active_treatment_2013 == 0 & wave == 13 & state == 2)
reghdfe life_satisfaction placebo_active_treatment_2013 [pweight=cws] if notreatvic13 == 0,
absorb(pid wave state) cluster(state)
outreg2 using Placebo_Tests.doc, append ctitle(2013)

* Define placebo treatment periods for 2015
gen placebo_treatment_reg_2015 = (intdate_dv >= 20207 & intdate_dv <= 20393) //
Equivalent to 06/08/2015 - 17/09/2015
gen placebo_treatment_metro_2015 = (intdate_dv >= 20079 & intdate_dv <= 20529) //
Equivalent to 09/07/2015 - 28/10/2015

gen placebo_active_treatment_2015 = 1 if placebo_treatment_reg_2015 == 1 & capital_area
== 29
replace placebo_active_treatment_2015 = 1 if placebo_treatment_metro_2015 == 1 &
capital_area == 21
replace placebo_active_treatment_2015 = 0 if placebo_active_treatment_2015 == .

gen notreatvic15 = (placebo_active_treatment_2015 == 0 & wave == 15 & state == 2)
reghdfe life_satisfaction placebo_active_treatment_2015 [pweight=cws] if notreatvic15 == 0,
absorb(pid wave state) cluster(state)
outreg2 using Placebo_Tests.doc, append ctitle(2015)

* Define placebo treatment periods for 2017
gen placebo_treatment_reg_2017 = (intdate_dv >= 20985 & intdate_dv <= 21171) //
Equivalent to 06/08/2017 - 17/09/2017
gen placebo_treatment_metro_2017 = (intdate_dv >= 20857 & intdate_dv <= 21307) //
Equivalent to 09/07/2017 - 28/10/2017
```

gen placebo_active_treatment_2017 = 1 if placebo_treatment_reg_2017 == 1 & capital_area == 29
replace placebo_active_treatment_2017 = 1 if placebo_treatment_metro_2017 == 1 & capital_area == 21
replace placebo_active_treatment_2017 = 0 if placebo_active_treatment_2017 == .

gen notreatvic17 = (placebo_active_treatment_2017 == 0 & wave == 17 & state == 2)
reghdfe life_satisfaction placebo_active_treatment_2017 [pweight=cws] if notreatvic17 == 0, absorb(pid wave state) cluster(state)
outreg2 using Placebo_Tests.doc, append ctitle(2017)

*************************** Alternative time windows around the treatment period Table 4

* Original lockdown period (without the extra two weeks)
gen lockdown_reg = (intdate_dv >= 22103 & intdate_dv <= 22175) // Assuming original lockdown end date for regional areas is 14 days before treatment_reg
gen lockdown_metro = (intdate_dv >= 22103 & intdate_dv <= 22189) // Assuming original lockdown end date for metro areas is 14 days before treatment_metro
gen active_treatment_lockdown = 1 if lockdown_reg == 1 & capital_area == 29
replace active_treatment_lockdown = 1 if lockdown_metro == 1 & capital_area == 21
replace active_treatment_lockdown = 0 if active_treatment_lockdown == .
reghdfe life_satisfaction active_treatment_lockdown [pweight=cws], absorb(pid wave state) cluster(state)
outreg2 using Lockdown_Period.doc, replace ctitle(Lockdown)

* Lockdown period plus 2 weeks
gen treatment_reg2=(intdate_dv>=22103 & intdate_dv<=22189)
gen treatment_metro2=(intdate_dv>=22103 & intdate_dv<=22230)
gen active_treatment2 =1 if treatment_reg==1 & capital_area==29
replace active_treatment2 =1 if treatment_metro==1 & capital_area==21
replace active_treatment2 =0 if active_treatment==.
reghdfe life_satisfaction active_treatment [pweight=cws], absorb(pid wave state) cluster(state)
outreg2 using Lockdown_Period.doc, append ctitle(Lockdown + 2)

* Lockdown period plus 4 weeks
gen lockdown_plus4_reg = (intdate_dv >= 22103 & intdate_dv <= 22217) // 4 weeks added to original lockdown_reg
gen lockdown_plus4_metro = (intdate_dv >= 22103 & intdate_dv <= 22244) // 4 weeks added to original lockdown_metro
gen active_treatment_plus4 = 1 if lockdown_plus4_reg == 1 & capital_area == 29
replace active_treatment_plus4 = 1 if lockdown_plus4_metro == 1 & capital_area == 21
replace active_treatment_plus4 = 0 if active_treatment_plus4 == .
reghdfe life_satisfaction active_treatment_plus4 [pweight=cws], absorb(pid wave state) cluster(state)
outreg2 using Lockdown_Period.doc, append ctitle(Lockdown + 4)

```
* Lockdown period plus 8 weeks
gen lockdown_plus8_reg = (intdate_dv >= 22103 & intdate_dv <= 22245)  // 8 weeks added
to original lockdown_reg
gen lockdown_plus8_metro = (intdate_dv >= 22103 & intdate_dv <= 22272) // 8 weeks added
to original lockdown_metro
gen active_treatment_plus8 = 1 if lockdown_plus8_reg == 1 & capital_area == 29
replace active_treatment_plus8 = 1 if lockdown_plus8_metro == 1 & capital_area == 21
replace active_treatment_plus8 = 0 if active_treatment_plus8 == .
reghdfe life_satisfaction active_treatment_plus8 [pweight=cws], absorb(pid wave state)
cluster(state)
outreg2 using Lockdown_Period.doc, append ctitle(Lockdown + 8)


* Whole 2020
gen treatment_whole_2020 = (year == 2020)
gen active_treatment_2020 = 1 if treatment_whole_2020 == 1 & capital_area == 29
replace active_treatment_2020 = 1 if treatment_whole_2020 == 1 & capital_area == 21
replace active_treatment_2020 = 0 if active_treatment_2020 == .
reghdfe life_satisfaction active_treatment_2020 [pweight=cws], absorb(pid wave state)
cluster(state)
outreg2 using Lockdown_Period.doc, append ctitle(Whole 2020)


**************************** Reverse Causality Test Table 5
* Not significant
reghdfe active_treatment life_satisfaction [pweight=cws] if notreatvic20==0, absorb(pid wave
state) cluster(state)
outreg2 using Reverse_Causality.doc, replace ctitle(Treatment)

**************************** DiD Effect per Age Group Table 6
* Create age group categories
gen age_group = .
replace age_group = 1 if age >= 15 & age <= 19
replace age_group = 2 if age >= 20 & age <= 29
replace age_group = 3 if age >= 30 & age <= 54
replace age_group = 4 if age >= 55 & age <= 69
replace age_group = 5 if age >= 70

* Regression for age group 15-19
reghdfe life_satisfaction active_treatment [pweight=cws] if age_group == 1, absorb(pid wave
state) cluster(state)
outreg2 using Age_Group.doc, replace ctitle("15-19")

* Regression for age group 20-29
reghdfe life_satisfaction active_treatment [pweight=cws] if age_group == 2, absorb(pid wave
state) cluster(state)
outreg2 using Age_Group.doc, append ctitle("20-29")

* Regression for age group 30-54
reghdfe life_satisfaction active_treatment [pweight=cws] if age_group == 3, absorb(pid wave
state) cluster(state)
```

```
outreg2 using Age_Group.doc, append ctitle("30-54")

* Regression for age group 55-69
reghdfe life_satisfaction active_treatment [pweight=cws] if age_group == 4, absorb(pid wave
state) cluster(state)
outreg2 using Age_Group.doc, append ctitle("55-69")

* Regression for age group 70+
reghdfe life_satisfaction active_treatment [pweight=cws] if age_group == 5, absorb(pid wave
state) cluster(state)
outreg2 using Age_Group.doc, append ctitle("70+")


**************************** DiD Effect per Gender Table 7
* Regression for Males (sex = 1)
reghdfe life_satisfaction active_treatment [pweight=cws] if sex == 1, absorb(pid wave state)
cluster(state)
outreg2 using Sex.doc, replace ctitle("Male")

* Regression for Females (sex = 2)
reghdfe life_satisfaction active_treatment [pweight=cws] if sex == 2, absorb(pid wave state)
cluster(state)
outreg2 using Sex.doc, append ctitle("Female")


**************************** DiD Effect per Family Types Table 8

* Regression for family type [1] Couple family without children or others
reghdfe life_satisfaction active_treatment [pweight=cws] if ftype == 1, absorb(pid wave state)
cluster(state)
outreg2 using Family_Type.doc, replace ctitle("Couple family without children")

* Regression for family type [4] Couple family with children < 15 without others
reghdfe life_satisfaction active_treatment [pweight=cws] if ftype == 4, absorb(pid wave state)
cluster(state)
outreg2 using Family_Type.doc, append ctitle("Couple family with children < 15")

* Regression for family type [13] Lone parent with children < 15 without others
reghdfe life_satisfaction active_treatment [pweight=cws] if ftype == 13, absorb(pid wave
state) cluster(state)
outreg2 using Family_Type.doc, append ctitle("Lone parent with children < 15")

* Regression for family type [24] Lone person
reghdfe life_satisfaction active_treatment [pweight=cws] if ftype == 24, absorb(pid wave
state) cluster(state)
outreg2 using Family_Type.doc, append ctitle("Lone person")

**************************** DiD Effect based on Mental Health scores Table 9

* Create mental health categories
gen men_health_category = .
```

replace men_health_category = 1 if men_health <= 33   // Low mental health
replace men_health_category = 2 if men_health > 33 & men_health <= 66   // Medium mental health
replace men_health_category = 3 if men_health > 66   // High mental health
label define men_health_lbl 1 "Low" 2 "Medium" 3 "High"
label values men_health_category men_health_lbl

* Regression for individuals with low mental health
reghdfe life_satisfaction active_treatment [pweight=cws] if men_health_category == 1, absorb(pid wave state) cluster(state)
outreg2 using Mental_Health_Influence.doc, replace ctitle("Low Mental Health")

* Regression for individuals with medium mental health
reghdfe life_satisfaction active_treatment [pweight=cws] if men_health_category == 2, absorb(pid wave state) cluster(state)
outreg2 using Mental_Health_Influence.doc, append ctitle("Medium Mental Health")

* Regression for individuals with high mental health
reghdfe life_satisfaction active_treatment [pweight=cws] if men_health_category == 3, absorb(pid wave state) cluster(state)
outreg2 using Mental_Health_Influence.doc, append ctitle("High Mental Health")

/////// This file is used for the Matching Process during the DiD Analysis

use

** Filling Missing Years, Assuming constant values for Big-5 and Risk Preference **

* Preserve and process 2020 data for Big-5 traits
preserve
keep if year == 2020

* Keep only the necessary variables and rename them for clarity
keep pid agreeableness extraversion conscientiousness emot_stability openness
rename (agreeableness extraversion conscientiousness emot_stability openness) (agreeableness_2020 extraversion_2020 conscientiousness_2020 emot_stability_2020 openness_2020)

* Save the 2020 subset as a temporary file
tempfile temp2020
save `temp2020'

* Restore the original dataset

```
restore

* Preserve and process 2017 data for risk preferences
preserve
keep if year == 2017

* Keep only the necessary variables and rename them for clarity
keep pid risk_preference
rename risk_preference risk_preference_2017

* Save the 2017 subset as a temporary file
tempfile temp2017
save `temp2017'

* Restore the original dataset
restore

* Merge the 2020 Big-5 values back into the original dataset
merge m:1 pid using `temp2020'

* Ensure the Big-5 values are properly replaced
replace agreeableness = agreeableness_2020 if _merge == 3
replace extraversion = extraversion_2020 if _merge == 3
replace conscientiousness = conscientiousness_2020 if _merge == 3
replace emot_stability = emot_stability_2020 if _merge == 3
replace openness = openness_2020 if _merge == 3

* Drop the temporary variables from the first merge
drop agreeableness_2020 extraversion_2020 conscientiousness_2020 emot_stability_2020
openness_2020 _merge

* Merge the 2017 risk preferences back into the original dataset
merge m:1 pid using `temp2017'

* Ensure the risk preferences values are properly replaced
replace risk_preference = risk_preference_2017 if _merge == 3

* Drop the temporary variables and merge indicator if no longer needed
drop risk_preference_2017 _merge

* Save the updated dataset
save


**********************************************************************************
**********************************************************************************
************************************************************************ Assessing
Collinearity and standardize variables
**********************************************************************************
**********************************************************************************
************************************************************************
```

```
* Standardize the variables
egen z_age = std(age)
egen z_num_child = std(num_child)
egen z_sex = std(sex)
egen z_employment = std(employment)
egen z_occupation = std(occupation)
egen z_risk_preference = std(risk_preference)
egen z_agreeableness = std(agreeableness)
egen z_conscientiousness = std(conscientiousness)
egen z_openness = std(openness)
egen z_emot_stability = std(emot_stability)
egen z_extraversion = std(extraversion)

* Correlation analysis * High correlation between occupation and employment
corr z_age z_sex z_occupation z_employment z_risk_preference z_agreeableness
z_conscientiousness z_openness z_emot_stability z_extraversion z_num_child

* Variance Inflation Factor analysis * Very low multicollinearity
qui reg z_age z_sex z_occupation z_employment z_risk_preference z_agreeableness
z_conscientiousness z_openness z_emot_stability z_extraversion z_num_child
estat vif


************************************************************************
************************************************************************
*************************************************************** Propensity
Score Matching
************************************************************************
************************************************************************
***************************************************************

* Estimate propensity scores
logit active_treatment z_age z_sex z_occupation z_employment z_risk_preference
z_agreeableness z_conscientiousness z_openness z_emot_stability z_extraversion
z_num_child
predict ps, pr

* Perform single nearest-neighbor matching with common support condition
psmatch2 active_treatment, pscore(ps) outcome(life_satisfaction) neighbor(1) caliper(0.05)
common

* Check balance
pstest   z_age z_sex z_occupation z_employment z_risk_preference z_agreeableness
z_conscientiousness z_openness z_emot_stability z_extraversion z_num_child, graph

* Create a new weight variable if needed
gen match_weight = _weight

* Check the distribution of weights and support indicator
sum match_weight _support
```

```
* List observations where _support is 1 to ensure they are correctly matched
list pid active_treatment ps match_weight _support if _support == 1, sepby(active_treatment)
noobs

***************** Saving the matched dataset
save


***********************************************************************
***********************************************************************
***********************************************************************
***********************************************************************
*********************** Main Model with Matching Weights
***********************************************************************
***********************************************************************
***********************************************************************
***********************************************************************
***********************

use /

* Run the main model with match weights, fixed effects, and clustered standard errors
reghdfe life_satisfaction active_treatment [pweight=match_weight], absorb(pid wave state)
cluster(state)
```

/////// This file is used for the Social Welfare Analysis comparing the lockdown policy to a Business-as-Usual scenario

```
******************************************************* Policy 1 =
Lockdown with expanded Data
clear all
use

///// Step 1: Predict Life Satisfaction Under Lockdown
reghdfe life_satisfaction active_treatment [pweight=cws], absorb(pid state year) cluster(state)
predict xb

///// Step 2: Filter for the treatment group (those under lockdown)
keep if active_treatment == 1

///// Step 3: Expand the dataset to represent the full population, resulting in 6.676.469 Obs
egen total_weight = total(cws)
gen scaled_weight = (cws / total_weight) * 6680000
expand scaled_weight, gen(replication_factor)
drop if replication_factor == 0

///// Step 4: Adjust the life satisfaction prediction to match the expanded population
gen scaled_life_satisfaction = xb
```

```
///// Step 5: Transform using Atkinson SWF:
gen ln_scaled_life_satisfaction = ln(scaled_life_satisfaction)

///// Step 6: Calculate the Total Life Satisfaction for the Population:
egen total_ln_life_satisfaction = total(ln_scaled_life_satisfaction)
display total_ln_life_satisfaction

****************************************************** Policy 2 = Business-as-Usual

clear all
use /

///// Step 1: Keep Control in 2020 to incorporate pandemic effects
keep if active_treatment == 0 & year == 2020

///// Step 2: Expand the dataset to represent the full population, resulting in 6.664.881 Obs
egen total_weight = total(cws)
gen scaled_weight = (cws / total_weight) * 6680000
expand scaled_weight, gen(replication_factor)
drop if replication_factor == 0

///// Step 3: Create Mortality Score and Assign Deaths
local additional_deaths = 44756 // Directly set the total number of additional deaths

*** 1) Normalize Age
egen max_age = max(age)
gen age_norm = age / max_age

*** 2) Adjust Health Status Variable
gen health_status_adj = 0
replace health_status_adj = 1 if long_term_health == 1

*** 3) Invert and Normalize Income
egen max_income = max(regular_income)
gen income_inverted = max_income - regular_income
egen max_income_inverted = max(income_inverted)
gen income_norm = income_inverted / max_income_inverted

*** 4) Generate Mortality Risk Score
gen mortality_risk = age_norm + health_status_adj + income_norm

*** 5) Normalize Mortality Risk Score
egen max_risk = max(mortality_risk)
gen mortality_risk_norm = mortality_risk / max_risk

*** 6) Assign Deaths Based on Mortality Risk *** 44,756 real changes made
gen additional_deaths = 44756
gen random = runiform()        // Generate a random number for tie-breaking
sort mortality_risk_norm random
```

```
gen death = 0                 // Initialize death variable
replace death = 1 if _n <= additional_deaths

///// Step 4: Atkinson Transformation:
gen ln_life_satisfaction = ln(life_satisfaction)

///// Step 5: Calculate the lost WELLBYs based on the life satisfaction scores of the deceased

***  1) Adjust Life Satisfaction for Deceased Individuals
gen adjusted_ls_deceased = ln_life_satisfaction - 2 if death == 1

***  2) Calculate Lost WELLBYs for Deceased Individuals
gen lost_wellbys_deceased = adjusted_ls_deceased * 6 if death == 1

***  3) Aggregate the Total Lost WELLBYs
egen total_lost_wellbys = total(lost_wellbys_deceased)
display total_lost_wellbys
gen total_lost_wellbys = 22691.6

///// Step 6: Calculate the sum of ln-transformed life satisfaction for the living population
keep if death == 0
egen total_ls_sum = total(life_satisfaction)
display total_ls_sum
gen total_ls_sum = 52388904

*** 2) Subtract the lost WELLBYs for deceased individuals from the living population's
welfare
gen social_welfare_bau = total_ls_sum - total_lost_wellbys

*** 3) Display the social welfare under Business-as-Usual scenario ***
display social_welfare_bau
```