Three Essays in Empirical Microeconomics

Zur Erlangung des akademischen Grades eines

Doktors der Wirtschaftswissenschaften
(Doktor rerum politicarum)

von der KIT-Fakultät für Wirtschaftswissenschaften

des Karlsruher Instituts für Technologie (KIT)

genehmigte

DISSERTATION

von

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Tag der mündlichen Prüfung:	12. November 2025
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Karlsruhe, November 2025

Abstract

This dissertation consists of three studies that apply diverse methodological approaches, including cross-national survey data, social media content analysis, and an online experiment, to explore individual behavior within the field of empirical microeconomics.

The first two studies are motivated by the global shock of COVID-19 pandemic, which triggered disruption in many aspects of life due to public health responses such as lockdowns. While prior research has examined pandemic-induced behavioral changes, much of it relied on single-country datasets, limiting the ability to generalize findings or assess how specific lockdown characteristics influence changes in behavior. The first two studies address this gap by employing cross-national data to provide a more comprehensive analysis of the impact of lockdown measures on the changes in daily habits. The first study investigates changes in hygiene habits – specifically, face mask usage and daily handwashing frequency – and people's long-term beliefs about the persistence of these changes after the pandemic. Using a representative survey across eight countries, together with Twitter and Google Trends analysis, it finds that both behaviors increased significantly during lockdowns. Long-term beliefs about these habits are sticky and do not fall back to the level before the pandemic. The results reveal that stricter lockdown leads to stronger responses. Lockdown lengths also contribute to an improvement in hygiene practices, but too long lockdown might backfire. Drawing on the same survey dataset, the second study focuses on the shifts in digital habits such as online streaming, remote work, online studying and digital gaming. The results show that both lockdown stringency and lockdown lengths are positively associated with changes in digital activities, however, the effect of lockdown lengths are not linear.

The third study departs from the pandemic context to explore a broader trend that it accelerated: the growing reliance on digital channels for financial advice. As in-person financial counselling declined during the pandemic, individuals increasingly turn to virtual sources for investment advice. This shift raises questions about the quality and consequences of online peer advice. To investigate this, the third study uses an online experiment to assess the impact of online advice, sourced from Reddit, on an investment task. The findings reveal that advice leads to improved investment quality. Moreover, individuals are more likely to choose advisors

with high past returns, even when doing so involves increased risk exposure. Individuals who could choose an advisor valued their portfolio more highly compared to those who made decisions by themselves, suggesting that access to advice can enhance both objective and perceived investment outcomes.

Overall, these studies contribute to our understanding of how exogenous shocks and emerging digital environments reshape behavior. By integrating survey research, social media analysis, and experimental methods, the dissertation demonstrates the methodological breadth and practical relevance of empirical microeconomics, offering insights for policy design and digital governance.

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1 Introduction

Economic research has become increasingly empirical, a trend documented by several scholars (Hamermesh, 2013; Angrist et al., 2017). At the forefront of this shift is empirical microeconomics (Angrist et al., 2017). Empirical microeconomics is a field that relies on data and statistical methods to examine individual and group decision-making, such as decisions related to consumption (Dynan et al., 2004; Johnson et al., 2006), labor supply (Angrist and Krueger, 1999), education (Card and Krueger, 1992*a*; Angrist et al., 2002), health (Currie and Gruber, 1996*a*; Finkelstein et al., 2012) and investment (Benartzi and Thaler, 2001). The aim is to estimate the causal effects of one factor on some outcomes of interest, which is achieved by credible identification strategies using surveys, large administrative records, or carefully designed randomized experiments. The development of the empirical approach in microeconomics has been driven, on the one hand, by the growing availability of new forms of datasets on individuals, households and firms, and on the other hand, by the improvement in computing power and speed (Heckman, 2001; Hashimzade and Thornton, 2021).

While theoretical microeconomics aims to develop abstract models of optimization and equilibrium to examine individual and firm behavior, empirical microeconomics focuses on measuring real-world behavior, with an emphasis on uncovering causal relationships that can test economic theories and evaluating public policies. Economic theories play a crucial role in guiding the construction of counterfactuals and providing a framework for interpreting empirical data. In recent decades, the field has undergone a methodological shift. Early empirical work often relied on cross-sectional data and correlations, which raised concerns about endogeneity issue (Angrist and Pischke, 2009). Endogeneity arises when the explanatory variable of interest is correlated with unobserved factors that also influence the outcome. This correlation can arise due to omitted variable bias, reverse causality, or measurement error. As a result, the estimated relationships may be biased and inconsistent, which undermines the validity of causal inference. For instance, estimating the effect of education on earnings may be biased if unobserved ability influences both schooling decisions and wages (Angrist and Krueger, 1999; Cameron and Trivedi, 2005).

In response to these limitations, the field has undergone a “credibility revolution” which has brought more attention to credible research designs and causal inference (Angrist and Pischke, 2010). The growing use of randomized controlled trials (RCTs) and experimental methods is central to this movement. RCTs and experiments address the issue of endogeneity by introducing exogenous variation in the treatment variable, where most factors which influence behavior are held constant and only the variable of interest is varied at a time. Experiments are a controlled data-generating process. Randomization of subjects into treatment is crucial for the identification of casual effects in RCTs and experiments (Croson and Gächter, 2010; Moffatt, 2020).

In some cases, experiments occur naturally. Natural events such as climate shocks, pandemics, or policy changes can generate exogenous variations for casual inferences (De Vocht et al., 2021; Vaci et al., 2025). For example, the COVID-19 pandemic and varied governmental responses have been considered as a large-scale natural experiment by several scholars (Islam et al., 2020; Lu et al., 2021; Goldberg et al., 2020; Prati and Mancini, 2021; Mansfield et al., 2022; Vaci et al., 2025). Unlike many life events, the pandemic affected billions of people simultaneously. The heterogeneity in governmental responses across countries and regions created a unique situation where one could study the effects of those responses on different outcomes such as economic impact (Inoue and Todo, 2020; Tellis et al., 2023) or social behavior (Lu et al., 2021; Prati and Mancini, 2021; Mansfield et al., 2022; Vaci et al., 2025). The first two studies of this dissertation are related to this strand of literature, where we examine the impact of COVID-19 lockdowns on the change of daily habits using across-national survey data.

Meanwhile, lab experiments have often been replaced by online experiments. This trend has been further pushed during the COVID-19 pandemic, when subjects were not allowed to physically enter the lab in many countries (Buso et al., 2021). Online experimental platforms such as Amazon Mechanical Turk (MTurk) and Prolific have expanded the reach and scalability of experiments. These tools allow researchers to test hypotheses with more diverse samples at relatively low cost and fast speed (see Arechar et al. 2018 for a methodological comparison of online and lab experiments, and Peer et al. 2021 for a comparison of data quality from different platforms). The validity of these tools has been demonstrated by the successful replication of classic experiments (Amir et al., 2012; Crump et al., 2013; Buso et al., 2021). The third study of this dissertation uses an online experiment to examine the impact of advice on financial decision-making.

The experimental method contributes to economic research in several ways. First, they offer a controlled environment to test theories. Notable examples include Smith (1962) for testing competitive equilibrium and Güth et al. (1982) for ultimatum bargaining games. In addition, experiments can provide insights for the design of new theories by establishing replicable empirical patterns (Friedman and Cassar, 2004). For instance, experiments show systematic deviations from standard rational choice models, which motivates the development of behavioral theories such as prospect theory (Kahneman and Tversky, 1979) and social preferences (Rabin, 1992; Fehr and Schmidt, 1999; Dufwenberg and Kirchsteiger, 2004). Furthermore, experiments are conducted for practical purposes to guide policies in industry or government (Friedman and Cassar, 2004).

In addition to RCTs and experiments, recent development in econometrics have provided researchers with quasi-experimental methods, such as instrumental variables, difference-in-differences and regression discontinuity designs, to address endogeneity issue (Angrist and Pischke, 2010). These approaches have allowed researchers to estimate causal effects even in the absence of random assignment as in a classical lab or field experiment (Angrist and Pischke, 2009).

Research in empirical microeconomics is often policy-driven. Questions of economic policies that can be addressed with data motivate much of the research in this field (Heckman, 2001). A body of influential literature has investigated the effects of policies in different domains such as health (Finkelstein et al., 2012), education policy (Card and Krueger, 1992*a*,*b*; Angrist et al., 2002; Angrist and Lavy, 2009), labor and income policy (LaLonde, 1986), tax policy (Chetty et al., 2014), and anti-poverty and social programs (Currie and Gruber, 1996*b*; Banerjee et al., 2015). The first two studies of this dissertation contribute to this broad literature by examining the impact of COVID-19 lockdowns on changes of habits.

There is a growing interest in using social media content to supplement survey data in social and economic research. Platforms such as Facebook, Twitter (now X) and Reddit provide rich and real-time insights into individual opinions, attitudes, emotions and behavior, which are less costly and more timely than traditional survey data (Schober et al., 2016). The general approach involves converting social media content into structured formats, such as sentiment scores, that can be integrated with or compared to survey data (Conrad et al., 2021). Several studies have compared social media content with survey data and found meaningful correspondence (O'Connor et al., 2010; Antenucci et al., 2014; Ceron et al., 2014; Pasek et al., 2018). For instance, Antenucci et al. (2014) developed a "job loss" index derived from the frequency of tweets containing key words such as "fired", "axed", "downsized" and "lost job". They demonstrate its effectiveness in predicting U.S. unemployment, as measured by initial claims for unemployment insurance. From 2011 to 2014, the index closely mirrored the official claims data, indicating a strong alignment between social media signals and labor market trends.

While all three studies in the dissertation contribute to the broad field of empirical microeconomics, they employ different empirical strategies and draw on varied data sources to address their respective questions. The first two studies rely on large-scale cross-national survey data to investigate the impact of COVID-19 lockdowns on the change of daily habits. In addition, the first study also incorporates complementary evidence from social media data and Google Trend analysis to increase the robustness of the findings. The third study adopts an online experiment to examine the effect of advice on financial decision-making. The advice on the investment task was elicited from social media platform Reddit, which was rated as the most popular platform for young adults to seek financial guidance. Collectively, these studies illustrate the methodological range and practical relevance of modern empirical microeconomic research.

The remainder of the introduction provides a brief overview of the background and related literature of the three studies, followed by a short summary of each study.

Research Background

The COVID-19 pandemic presents a unique case for empirical microeconomic analysis. As a global, exogenous shock that affected virtually every aspect of life, it generated massive behavioral, institutional, and policy responses—often implemented rapidly, and with significant variation across countries. These conditions motivate the first two studies of this dissertation, where we examine how individuals adapt their behavior and beliefs in response to the pandemic, and how those adaptations may persist in the long term.

First identified in December 2019 in Wuhan China, the novel coronavirus (SARS-CoV-2, known as COVID-19 virus) rapidly evolved into a global health emergency. Early epidemiological studies showed that patients can become infectious before showing any symptoms, and there was an exponential rise in the number of cases since the identification of the virus (Chen and Yu, 2020). This triggered widespread concerns about its fast transmission and high reproduction rate. By March 2020, local transmission had been documented in more than ten countries outside China, despite its extensive containment efforts including isolation, contact tracing, and public education campaigns (European Centre for Disease Prevention and Control, 2020; World Health Organization, 2020).

The implementation of public health strategies was necessary to limit the spread of COVID-19 virus, and governments across the globe employed various non-pharmaceutical interventions to combat the disease. Among the most significant were national lockdowns, which included stay-at-home orders, business and school closures, travel restrictions, and limitations on public gatherings. The major advantage of the lockdown is its ability to reduce transmission rates and lower mortality, especially in the absence of effective vaccines or treatments (Woc-Colburn and Godinez, 2022). Countries such as China implemented very strict quarantine and lockdown policies. Meanwhile, Sweden was among the few countries that opted against strict lockdown measures and instead relied more on voluntary mitigation strategies (Björkman et al., 2023). Previous literature has sought to evaluate the effectiveness of lockdown measures. Studies have shown that early and stringent restrictions reduced transmission rates (Ferguson et al., 2020; Hsiang et al., 2020; Alexander et al., 2020), though debates remain about their optimal design, timing, and trade-offs (Yousefpour et al., 2020; Filipe et al., 2022).

Although these interventions played a significant role in managing public health risks, they also resulted in profound disruptions to social and economic life. For example, mobility and physical activities declined (Knell et al., 2020; Maltagliati et al., 2021), and new behavioral norms—such as remote work (Mouratidis and Papagiannakis, 2021; Belzunegui-Eraso and

Erro-Garcés, 2020), online learning (Dhawan, 2020; Hermawan, 2021), and enhanced hygiene practices (Ali et al., 2023)—emerged widely. Domestic violence increased during the lockdown period (Piquero et al., 2021), as did anxiety, depression, and other mental health disorders, particularly among individuals who are already vulnerable due to pre-existing conditions and social isolation (Rossi et al., 2020). Lockdowns also led to a significant decrease in GDP and an increase in unemployment rate in many countries (Greyling et al., 2021; Dreger and Gros, 2021; Brodeur, Gray, Islam and Bhuiyan, 2021).

Against this backdrop, the motivation for the first two studies in this dissertation is twofold: to contribute to our understanding of how individuals adapt to large-scale policy shocks, and to assess the long-term implications of these behavioral changes. Specifically, the first two studies investigate how COVID-19 lockdowns changed people's daily habits—with first study focusing on hygiene habits and the second on digital habits—and whether people expect these shifts to persist over time.

There are several reasons why this is important. From a policy perspective, behavioral adaptations such as remote work and online learning have lasting implications for labor market dynamics, urban infrastructure, and digital inequality. From a theoretical standpoint, the crisis provides a rare opportunity to test models of habit formation and adjustment under extreme uncertainty. And from a practical angle, understanding the adoption and persistence of hygiene practices has direct relevance for public health sector, hospitality and service sector. Maintaining good hygiene standards has become a critical factor in consumer satisfaction, as people increasingly prioritize cleanliness in their decision-making (Yang et al., 2024; Pereira et al., 2023). Businesses that adapt to these increased expectations are more likely to thrive in a post-pandemic environment.

The COVID-19 pandemic also altered the degree to which individuals seek and use professional financial advice (Rabbani et al., 2021). Research shows that there was a sharp reduction in in-person financial advice counseling and the majority of financial planners in the US now practice virtual financial planning (Fox and Bartholomae, 2020; Lamdin, 2020). In addition, individuals, especially young adults, increasingly turn to alternative sources such as social media platforms Reddit for peer-based financial advice.

This shift raises questions about the quality and consequences of online financial advice. On the one hand, social media allows users to access a broad pool of advice and potentially identify advisors whose investment styles align with their own risk preferences. On the other hand, individuals seeking for advice may be tempted to follow advisors with exceptionally high past returns, and consequently end up approaching advisors with a tendency to suggest investments with high exposure to risk. This could potentially lead to suboptimal financial outcomes. Although prior research has documented that social media features on trading platforms influence investment behavior (Dorfleitner and Scheckenbach, 2022; Heimer and Simon, 2015; Pelster and Hofmann, 2018; Deng et al., 2024), there remains a gap in understanding the welfare implications of online peer-to-peer financial advice. To address this gap, the third study employs an online experimental design, allowing for causal identification of the effects of peer advice from online social media platform on investment decisions.

This dissertation makes a multifaceted contribution to the field of empirical microeconomics, both in terms of substantive findings and methodological innovation. A key strength of the thesis lies in its methodological breadth, combining large-scale cross-country survey data, social media analysis, and experimental design to investigate individual behavior.

Research Summary

Summary of Study 1

The first study "**Hygiene habit change and sticky long-term beliefs during lockdowns**" analyses the impact of COVID-19 lockdowns on the change of hygiene habits, namely, the likelihood of wearing face masks during illness and daily hand-washing frequency.

During the Corona crisis, many habits have changed. Hygiene habits such as wearing masks and washing hands have become very important. We compare these habits with others, such as digital habits, that have changed as well. We also study long-term beliefs about these habits. The analysis is based on three sources of data: a quota-representative cross-national survey, a large-scale Twitter content analysis, and Google Trends data. The quota-representative survey includes a total of 17,728 respondents from 8 countries across the globe, which include China, South Korea, U.S., Germany, Sweden, New Zealand, Brazil and South Africa. The tweet analysis includes around 9.4 million tweets.

The survey measures the change of habits by examining the time spent on various activities in three distinct periods: before Corona, during the strictest lockdown, and people's expectations after Corona, that is, when the pandemic has ended. The short-run change of habits is measured by the difference between the time spent on an activity per day during the strictest lockdown and that before Corona. The long-run change is measured by the difference in the time spent on the activity in expectation after Corona and that before Corona. In the context of hygiene habits, we measure the change in the likelihood of wearing face masks when feeling sick and the change of the daily hand-washing frequency across the three periods. As a measure of the strictness of the lockdown policies, we use the number of self-reported governmental interventions out of 11 listed restrictions during the strictest lockdown. We estimate random-effect regression models to determine the effects of lockdowns, namely, its strictness and the self-reported lockdown length, on changes of habits both in the short run and in the long run.

The survey results show a significant increase in the acceptance of mask-wearing and in the frequency of handwashing. People expect to stick with improved hygiene habits after the pandemic. For mask wearing, the expected change is stronger and longer lasting than for many non-hygiene habits, including digital habits. This is also confirmed by Twitter and Google Trend analysis. We find an upward trend in the share of tweets referring to wearing masks and hand washing when the pandemic reached U.S. Thereafter, there was a gradual shift in the share of tweets from hand washing towards wearing masks. After June 2020, the average share of tweets referring to hand washing returned almost back to the level from before the pandemic. Consistent with our analysis of social media posts from Twitter, the search query volumes of keywords related to hygiene habits on Google Trends also show an early upward trend for hand washing when the pandemic reached the U.S. Thereafter, we again observe a shift from hand washing towards wearing face masks. The search volume index for face masks peaked during the stay-at-home period in April 2020.

Furthermore, the survey results indicate that lockdown works. Imposing stricter lockdown leads to stronger responses, but too long lockdown might backfire, potentially by crowding out intrinsic motivation and civic virtue. Long term beliefs on habit change after the lockdown remain sticky and do not fall back to the level before the pandemic. Our results suggest that hygiene standards could be key for many businesses such as in the sales and hospitality sector, even in the long run.

Summary of Study 2

The second study "**Digital habit change during COVID-19 lockdowns and people's long-term expectation of habit change**" draws on the same survey dataset as Study 1 to examine the impact of COVID-19 lockdowns on the change of digital habits and people's long-term expectation on the persistence of habit change. In particular, this study explores changes in time spent on five key domains of online activity: general internet use, streaming services, teleworking or online studying, video call platforms, and online gaming.

Our analysis shows that people substantially increased the time spent on online activities during lockdowns compared to the period before Corona. Regression results indicate that both the strictness and duration of lockdowns are significantly associated with greater change in online behavior. However, the effect of lockdown length is nonlinear. Specifically, very long (i.e. more than 20 weeks) lockdowns showed diminishing effects. These findings suggest that the social and psychological pressures of lockdowns may have contributed to digital adaptation, though excessively prolonged restrictions may reduce their incremental impact.

In addition, we also examine whether people expect these changes to persist when Corona is not a pressing issue anymore. Respondents generally anticipated that their digital habits would remain elevated even after the pandemic, particularly in areas like teleworking and video communication.

Finally, we analyze whether changes in digital habits vary across sociodemographic groups. Regression results indicate that age, employment status, education, household size, and risk attitudes significantly influence both the extent of the changes of digital behaviors and expectations for the persistence of the changes.

Summary of Study 3

The third study "**Advisor selection and its impact on financial decision-making**" analyses how peer online advice elicited from social medial Reddit influences financial decision-making in an online experiment. Specifically, the study examines the impact of online advice on investment quality and the level of risk-taking. In addition, it also investigates the welfare implications of receiving advice.

Online financial advice intersects with several social phenomena, such as advice-giving and advice-seeking behavior (Kramer, 2016; Agnew et al., 2018), peer effects in risk-taking (Gortner and van der Weele, 2019; Gioia, 2017), and social interactions on online trading platforms (Dorfleitner and Scheckenbach, 2022; Heimer and Simon, 2015). These topics have received substantial attention in recent literature. However, a unique aspect of online advice that remains underexplored is the simultaneous presence of three key elements: the ability to choose an advisor, the possibility of selecting an objectively suboptimal portfolio, and the role of subjective risk preferences in determining optimal decisions. Our study design enables us to isolate the effect of advisor choice on both portfolio selection and perceived welfare, thereby assessing its overall impact on subjective well-being.

To address these questions, we conduct an online experiment in which subjects are asked to build a portfolio consisting of a mix of three artificial assets. One of these assets is first-order stochastically dominated by a combination of the other two. Specifically, two of the assets are risky and perfectly positively correlated. The third asset is risk-free. The investment task is designed in a way that the less risky of the two correlated assets is dominated by a mixture of the riskier and the safe asset. Hence, the optimal choice depends on both a correct understanding of the dominance relationship (i.e., avoiding the dominated asset) and individual risk preferences (which determine the allocation between the safe and risky assets). Subjects in the control group make the investment decision by themselves, and subjects in the treatment group can choose one out of a list of advice before making the decision. Advisors are recruited from Reddit and are given time to practice the same investment task before giving advice.

We find evidence supporting both hypothesized effects of advice: improving investment quality and increasing risk exposure. Results reveal that subjects in the control group exhibit a strong tendency toward naive diversification. Naive diversification is a strategy where individuals divide their investments among highly correlated assets, and mistakenly believe that this reduces portfolio risk. This behavior is well-documented in pension fund choices (Benartzi and Thaler, 2001). In our setup, it implies splitting the investment between the two correlated risky assets, rather than between the undominated risky asset and the safe asset. In contrast, subjects in the treatment group are less prone to naive diversification. They invest less in the dominated asset and more frequently select fully undominated portfolios. However, these portfolios tend to be riskier in terms of worst-case outcomes. Importantly, treated subjects do not follow advice blindly. Instead, they consider their own risk preferences and tend to select advisors with similar risk attitudes. Nearly half of the treated participants modify the suggested portfolios to reduce perceived risk. Unfortunately, these adjustments often fail to meaningfully reduce downside risk and may even limit potential returns, as some parts of naive diversification persist. Nevertheless, even when treated subjects make suboptimal changes to the advised portfolios, they still achieve better outcomes than those in the control group.

To evaluate the overall welfare effect of the access to investment advice, we elicit the certainty equivalents of participants' chosen portfolios. On average, subjects exposed to advice report higher valuations of their portfolios. While this effect is not statistically significant in the full sample, it becomes significant among individuals whose choices are consistent with expected utility theory. The notion that access to advisor choice enhances welfare is further supported by observed changes in portfolio composition across treatments. Specifically, a greater proportion of treated subjects allocate at least part of their endowment to the safe asset compared to the control group. Any increase in risk exposure primarily results from reallocating funds from the dominated to the undominated risky asset. Furthermore, simulation results indicate that a substantial portion of untreated subjects would benefit from receiving advice, while only a small share of treated subjects are adversely affected by it.

2 Hygiene Habit Change and Sticky Long-Term Beliefs during COVID-19 Lockdowns

2.1 Introduction

Proper hygiene has always mattered for many businesses – be it restaurants, sales, factories, or the traveling industry. Peaksales, a recruiting company, wrote in 2013 that to win over customers, salespeople should invest in grooming and looking clean (Burdett, 2013). Back then, this included clean teeth, nails and breath. Adherence to hygiene standards is also an important factor which influences customers' choice of restaurants (Aksoydan, 2007; Jin and Leslie, 2009). Cleanliness of food, cutlery, service personnel, lavatory and kitchen all affect customers' perception of a restaurant (Aksoydan, 2007).[1] With the Corona pandemic, these hygiene standards may increase substantially, and changes may persist in the long run. For example, customers may attach greater importance to hygiene codes in service and hospitality sectors since it is crucial in reducing the chance of transmitting disease (Luo and Xu, 2021).

An increase in hygiene codes could be observed in many Asian countries during and in the aftermath of SARS1. Since then, wearing masks has become a norm for people using public transport while having a cold or influenza-like symptoms in many Asian countries (Lau et al., 2005; Burgess and Horii, 2012; Wada et al., 2012). Previous review studies also show that people improved their hand hygiene during the SARS1 outbreak and compliance with hand washing remained a high level after the crisis (Fung and Cairncross, 2007). To cope with

[0] This chapter is joint work with Jella Pfeiffer, Nicolas Pröllochs and Nora Szech.

[1] However, when authenticity and hygiene codes are in conflict, research shows that customers may overlook hygiene standards in restaurants which are considered as very authentic (Lehman et al., 2014).

the SARS1 crisis, managers in Hong Kong took proactive actions to sanitize their restaurants, and many even used cleanliness and hygiene as a selling point to attract more customers and to gain customers' trust (Alan et al., 2006). In contrast to SARS1, the Corona pandemic has severely impacted all regions across the globe. In this paper, we study how habits and long-term expectations shift because of the Corona pandemic in many different regions worldwide.

We study habits during the Corona crisis as well as long-time beliefs. We focus on two easily measurable hygiene habits: wearing masks and washing hands. We compare these to other habits that possibly changed during Corona as well, such as teleworking and online streaming. Hygiene habits display a drastic increase that is expected to last to significant extent. For example, we find in our data that hand washing increases by 43.59% during the crisis and is expected to be more than 30.77% after the Corona crisis compared to before the crisis. In most regions we study, masks were uncommon in public life before Corona. But even in regions like China, where masks were sometimes seen in public before, the likelihood of mask wearing increases by 1.43 scale point on a scale from 1-7 during Corona and is expected to be 1.15 scale point higher after the crisis than before the crisis.

We also analyse the impact of governance as well as of personal characteristics on hygiene habit change and expectations. This can be informative for management. We see that females are more willing to take up stronger hygiene habits. Moreover, enforcing, instead of only recommending, a new hygiene habit like mask wearing increases short-term uptake, but also long-time belief on hygiene habits.

Our findings are based on three sources. First, we run a quota-representative and partly incentivized questionnaire from 16 different regions from 8 different countries all over the world. This leads to a sample of 17,728 participants. In this main source for our analysis, we ask people about their habits, but also about their long-term expectations for after the crisis. Second, we study tweets on Twitter (now X) from the US (around 9.4 million Tweets). Tweeting reflects topics and information that users like to seek and share (Whiting and Williams, 2013). If they choose to tweet about hygiene or other habits, this shows that they engage in these topics. We see that people tweet a lot about habits that increase during Corona, such as teleworking and video conferencing. Hand-washing leads to a similar pattern on Twitter. But no reaction in tweets about habits is as strong and long-lasting as the increase in mask wearing tweets.

Third, we study data from Google Trends confirming our findings that interest in hygiene habits changes significantly.

2.2 Literature Review

Different approaches have been discussed in order to fight disease and infection in the Corona pandemic. Nudges (Thaler and Sunstein, 2009) show promise. For example, Milkman et al. (2021) demonstrate in a "mega-study" that some text messages work specifically well in order to motivate people to take a flu vaccine. The hope is these messages may also increase Corona vaccine demand. Relatedly, Beshears et al. (2016) demonstrate that more people take a flu vaccine if they do not have to make detours to get it. In a similar spirit, Serra-Garcia and Szech (2023) show that compensating people for taking a Corona vaccine increases vaccine intentions. Pre-scheduled appointments, rendering vaccination the default, help as well. Another widely introduced tool to curb Corona infection is the digital tracing apps. Yet, privacy concerns might impede its adoption in many countries. Munzert et al. (2021) show that small monetary incentives could strongly increase uptakes. Thus, both neoclassical and behavioral approaches can be successful. Also institutional design may help tremendously. Cramton et al. (2020) propose market mechanisms to allocate scarce goods in this crisis. Pathak et al. (2021) discuss the optimal matching of resources in overwhelmed hospitals. Więcek et al. (2021) develop optimal stretching schemes of vaccines in order to save as many lives as possible. Our data contribute the blunt insight that law can help to overcome this crisis as well. Imposing mask wearing increases take-up and habit formation. Thus, here, we have an example where law supports a pro-social habit formation in this crisis (Carlin and Bowles, 2020). Yet, our data also document that governmental interventions should not be too excessive in length, possibly to keep a cooperative spirit in citizens.

In response to the pandemic, many countries have adopted different degrees of lockdowns to prevent the spread of the virus, from social distancing to stay-at-home order. There is a growing body of literature examining the impacts of COVID-19 lockdowns. For instance, Fang et al. (2020) use cellular phone data to identify the causal effect of Wuhan lockdown on the transmission of COVID-19 and find the lockdown contributed substantially to reducing the total infection number outside Wuhan. Using mobile phone and survey data, Barrios et al. (2021) show voluntary social distancing maintained prevalent in high civic capital counties after US states began re-opening. In a similar vein, Alexander et al. (2020) find the stay-at-home order effectively reduced county-level mobility in the US. However, this was accompanied by a large reduction in consumer spending in restaurants and retail sectors. Aum et al. (2021), Birinci et al. (2021), Chodorow-Reich and Coglianese (2021), Coibion et al. (2020), Crossley et al. (2021), Goolsbee and Syverson (2021) and Gupta et al. (2020) also investigate the impacts of the pandemic and lockdowns on the labor market and the economy. Brodeur, Clark, Fleche and Powdthavee (2021) use Google Trends data to investigate individual well-being in times of lockdowns and they find a significant increase in the search volume for worry, loneliness and boredom. Our paper contributes to this strand of literature by investigating the impacts of lockdowns on people's daily habits and its long-term implication.

Our study contributes to the growing body of literature examining behavioral changes during COVID-19 lockdowns. Research has consistently found that self-reported physical activity levels declined during lockdowns, with the most significant reductions observed among individuals with well-established pre-lockdown routines (Knell et al., 2020; Maltagliati et al., 2021). At the same time, optimism and collective resilience were identified as key drivers of positive health-related behavior changes during this period (Guèvremont et al., 2022). Changes in dietary habits during lockdowns have also received attention and several studies documented shifts in food consumption patterns (Dixit et al., 2020; Di Renzo et al., 2020). Ananda et al. (2023) demonstrates a significant reduction in food waste during lockdowns, accompanied by notable improvements in food planning, purchasing, and storage. In a two-sector model, Bambi et al. (2024) show that the demand for products from sectors affected by the lockdown could either decrease or increase relative to pre-pandemic levels, depending on lockdown duration and habits' strength. Additionally, Salon et al. (2021) highlights the pandemic's potential to induce lasting behavioral shifts in the United States, such as increased telecommuting and reduced air travel. In contrast to previous literature, this study integrates survey analysis with social media and Google Trends data, offering external validation for the survey findings.

One popular lockdown measure that was implemented in many countries is obligatory face mask wearing. Empirical evidence has shown that face masks can effectively reduce the chances of both transmitting the coronavirus and getting infected by the virus, which could save many lives during the COVID-19 pandemic (Chan et al., 2020; Leung et al., 2020; Peeples, 2020; Howard et al., 2021). For example, Leffler et al. (2020) looked into 196 countries and found that weekly increases in per-capita COVID-19 mortality were approximately four times lower in regions with norms of mask wearing or mandatory mask-wearing policies, compared to other regions. Lyu and Wehby (2020) shows in a natural field experiment that mandating the use of face masks in public results in a greater drop in daily COVID-19 growth rates in the US, controlling for other governmental interventions such as social distancing. Abaluck et al. (2022) shows that in-person reinforcement of mask wearing led to increase in mask usage and a decrease in reporting COVID-like illness. In light of these findings, our data show that strict lockdown measures, especially the mandates of wearing masks in public, might lead to a transition into a new hygienic habit of mask wearing also in the long run. This could be valuable to protect societies from other infectious diseases, limit the spread of future pandemics and improve public health.

In the beginning of the Corona pandemic, masks were discussed controversially in many non-Asian countries. For example, there was debate on whether masks would make people less cautious such that they reduce social distancing behaviors. If so, imposing masks could backfire. Yet Seres et al. (2020) demonstrate in a field study that to the contrary, mask wearing increases social distancing. Thus, masks can help overcoming infection both, via a direct and an indirect effect. Mitze et al. (2020) also document that mask wearing reduces infections in this crisis. Zhang et al. (2020) suggest that airborne transmission is the major route for Corona infection. Luckily, we see in our data that not only short but also long-term habits seem to adapt well to mandatory mask wearing. Thus, businesses and states may be well advised to impose measures of hygiene when considered helpful.

Besides wearing face masks, proper hand washing is another easy way to remove germs and to reduce the risks of catching infectious diseases (Aiello et al., 2008). It is recommended that people should regularly wash their hands with soap and water and scrub for at least 20 seconds to prevent the spread of the coronavirus. Many health authorities also suggest people to sing the Happy Birthday Song twice as they wash their hands to keep track of time (Centers for Disease Control and Prevention, 2020; Godin, 2020). Following this hygienic rule not only reduces the risks of getting ill during the pandemic, but it also provides long-term benefits if people stick with it after the crisis. Using machine learning technique, Buyalskaya et al. (2023) investigate the habit formation of hand-washing in hospital and find that it takes weeks to form this habit. Our data provide evidence for an improved hand hygiene habit during COVID-19 lockdowns and people expect to stick with it to a large extent when the pandemic is over.

2.3 Data

This section outlines the data sources used in the study, which comprise three components: survey responses, social media content from Twitter (now known as X), and search interest data from Google Trends.

2.3.1 Survey Data

Survey data collection started on June 15, 2020 and concluded on June 29, 2020. We gathered 17,728 observations for the survey with samples being representative in terms of age and gender distribution for the regions of interest, which includes California, Texas, Florida, New York State, USA as a whole, five regions in China (Wuhan City, other cities in Hubei Province, Henan Province, Guangdong Province, Beijing), South Korea, Germany, Sweden, New Zealand, Brazil and South Africa. In China, we have to focus on younger people because the survey is done online and the internet penetration rate among older people in China is low (Dynata, 2022). Details of the sample are shown in Appendix A.1.1. We chose these regions because there is a large variation in terms of how local governments responded to the pandemic, and the strictness of the lockdowns differed across regions. Moreover, our sample consists of participants from six different continents.

The survey measures habits by asking the amount of time spent on different activities before Corona, during the strictest lockdown, and people's expectation after Corona, that is, when the pandemic has ended. In particular, (i) before Corona, (ii) during the strictest lockdown and (iii) after Corona were described as (i) the months leading up to the outbreaks, (ii) the period where participants experienced the strictest constraints, and (iii) a future time when Corona is no longer a pressing issue and life has returned to "normal". The survey also contains incentivized questions and questions regarding changes in hygienic habits, spending habits, employment status and financial situation. In this paper, we mainly focus on the change of habits with a specific focus on hygiene habits.

2.3.2 Social Media Posts from Twitter

Our second data source to analyze the formation of habits are social media posts from Twitter (now X). We chose Twitter as it is a leading social media platform that enjoys widespread popularity (Pew Research Center 2016). During the COVID-19 pandemic, Twitter had around 320 million active users (Statista, 2022).

We employed the Twitter API to collect a time series of random tweets from four U.S. states, namely, California, Florida, New York, and Texas (see Appendix A.3.1 for details). Since we are interested in how habits evolve over time, we did not restrict the API calls to any sets of predefined keywords but rather collected random samples of all publicly available English-speaking tweets. The four crawlers (one crawler per location) collected tweets in the timeframe between the last week of January 2020 (i.e., the week in which the WHO declared an emergency of international concern (WHO 2020) and end of July 2020, i.e., for a period of six months. The crawlers collected 500 random tweets each hour, which resulted in 500 x 24 tweets per day for each of the four U.S. states. The total number of tweets in our dataset is around 9.4 million.

Subsequently, we employed state-of-the-art methods from machine learning and natural language processing to predict whether individual tweets in our dataset refer to a certain habit. Specifically, we trained (and validated) a machine learning model to predict fine-grained habit labels (e.g., Face masks, Hand washing) for each of the 9.4 million tweets in our dataset (see Appendix A.3.2 for details). The machine learning classifier yielded a high macro $F1$-score of 0.80 and a classification accuracy of 79.10%, which can be regarded as state-of-the-art performance when it comes to fine-grained classification of tweets Yao et al. (2020). We use these machine learning-labeled tweets to analyze how the share of tweets referring to habits changed over the course of the pandemic.

2.3.3 Google Trends Data

We complement our analysis of social media posts on Twitter by studying how Google search volumes have changed over the course of the pandemic. For this purpose, we employed the Google Trends API to collect search query volumes for keywords that are related to habits (see list of keywords in Appendix A.3.3). For example, for the habit "Face masks," we query terms such as "wear mask" "face mask," "mask distancing," etc.

Analogous to our analysis of tweets, we collected the search query volumes in the timeframe between January 2020 and end of July 2020 across four different U.S. states, namely, California, Florida, New York, and Texas. The result of the data collection are multiple weekly time series of the volume of search queries users enter into Google Search in a given geographic area for a given habit.

2.4 Results

In this section, we present the empirical findings of our study, drawing on the combined evidence from survey responses, tweet content, and Google trends.

2.4.1 Survey Results

Face Masks

To elicit the habit of wearing face masks, we asked participants on a 7-point Likert scale how likely they were to wear face masks during illness before Corona, during lockdown (if applicable) and their expectation after Corona (1="extremely unlikely"; 7="extremely likely"). As illustrated in Figure 2.1, there is a drastic increase in the acceptance of wearing face masks in time of illness during lockdowns compared to the level before the pandemic, and this shift in attitudes seems to persist even after Corona. Figure 2.2 further indicates that the persistence of the change in face mask wearing is stronger in regions where face masks were mandatory in certain public areas during the pandemic. On average, respondents who reported governmental mandates of public mask wearing during the pandemic expect to increase the likelihood rating of wearing face masks when feeling sick by 1.7 scale points after Corona compared to before Corona. In contrast, those who reported no policy on face masks expect to increase the likelihood by 1 scale point. The difference between the two groups is statistically significant according to a two-sided t-test ($p < 0.001$, n =17,728).

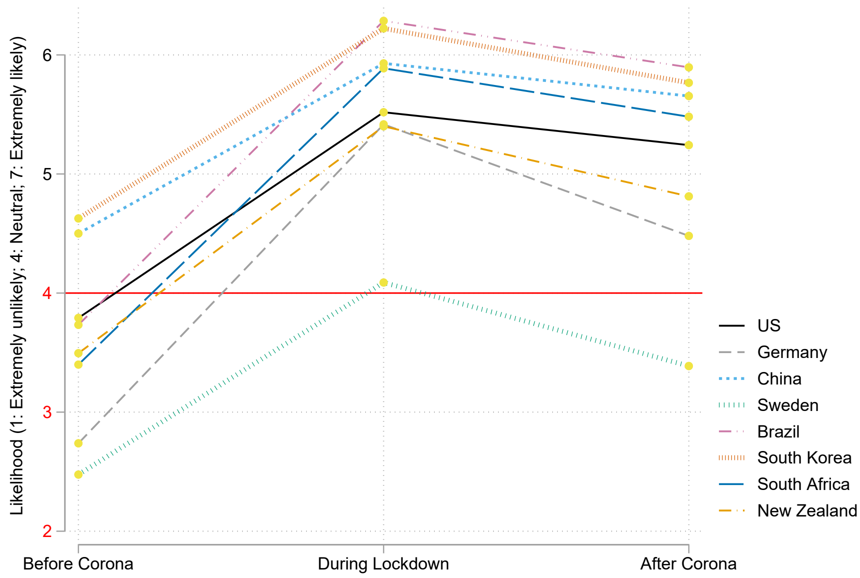


Figure 2.1: Likelihood of wearing face masks when feeling sick. The figure shows the average rating of the likelihood of wearing face masks (7-point Likert scales) by time period and country. The red line represents the switching line from being unlikely to wear face masks to being likely to wear face masks.

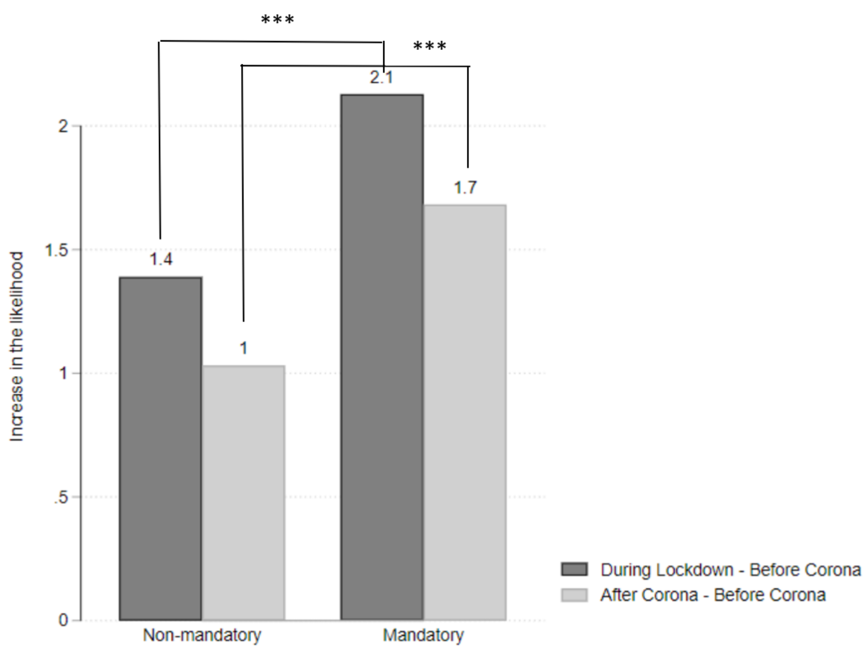


Figure 2.2: Likelihood of wearing face masks and mandatory policy of face masks. The figure shows the average increase in the rating of the likelihood of wearing face masks by whether face masks are mandatory in certain public areas during the lockdown. The change is significantly lower among people who reported no mandatory policy of wearing face masks compared to those who experienced mandates of public mask wearing. (two-sided t-test, p<0.001, n=17,728)

Norms on face mask wearing differed between some east Asian countries and other countries prior to the pandemic. The majority of the respondents from China and South Korea reported being likely to wear face masks when feeling sick before Corona, whereas most respondents from other countries expressed an unwilling or neutral attitude. More than 70% of the respondents from countries other than Sweden, which took a comparatively lenient approach to the crisis, reported that they were likely to wear face masks when feeling sick during lockdowns and more than half of the respondents in these countries expected that they would continue to do so after Corona (see Figure A.1 in Appendix A.1.2).

We estimate random-effect regression models to determine the effects of lockdowns on changes of habits both in the short run and in the long run. The short-run change of wearing face masks for each survey participant i is measured by the difference between the likelihood rating of wearing face masks when feeling sick during lockdown and that before Corona. The long-run change is measured by the difference in the likelihood of wearing face masks in sickness in expectation after Corona and that before Corona. We regress the change in the responses ($HabitChange_{i_c}$) on the strictness of the lockdown and the self-reported lockdown length respectively[2]. The strictness of the lockdown is measured by the number of self-reported governmental interventions out of 11 listed restrictions during the strictest lockdown (see Appendix A.1.4). In our regression models, we control for the following individual characteristics of each participant (X_i): age, gender, marital status, education level, employment status, household size, financial stress level during lockdowns, risk attitude in general, risk attitude in health-related issues, perceived health status, whether there are kids at home and whether there are elderly aged above 65 at home. In addition, we control for heterogeneity across countries through the use of country-specific random effects.

The regressions take the following form:

$$HabitChange_{i_c} = \beta_0 + \beta_1 LockdownStrictness_i + \beta_3^T X_i + u_c \tag{2.1}$$

[2] The variable lockdown length is defined as 7 categories: 0 week, 1-5 weeks, 6-10 weeks, 11-15 weeks, 16-20 weeks, more than 20 weeks and unknown lockdown length, with 0 week (i.e. no lockdown) being the reference category.

$$HabitChange_{i_c} = \beta_0 + \beta_2 LockdownLength_i + \beta_3^T X_i + u_c \tag{2.2}$$

with parameters $\beta_0, \ldots, \beta_3$ (out of which β_3 is a vector), and country-specific random effect u_c.

Short-term Analysis The data show that the change in the likelihood of wearing face masks is highly driven by the strictness of lockdown. On average, as the number of self-reported bans increases by 1, the increase in the rating of the likelihood of wearing face masks increases by 0.12 scale point during lockdowns compared to before Corona, controlling for country random effects (p<0.01, see Table 2.1 Column 1). The length of the strictest lockdowns also plays a role in reshaping the habit of face mask wearing. On average, participants who reported a lockdown of one to five weeks increase the likelihood of wearing face masks more than those who reported no lockdowns by 0.48 scale point during lockdowns compared to before Corona (p<0.01, see Table 2.1 Column 2). However, the relationship is not linear. The coefficients for lockdown length dummies decrease with reported lockdown length and the change in responses from people who reported a lockdown length between 16-20 weeks does not differ significantly from those who reported no lockdown. In line with Carlin and Bowles (2020), our data suggest that governmental interventions work best if implemented with moderation such that citizens' cooperative spirit is encouraged instead of overstretched.

To further investigate the policy response, we regressed the change in the likelihood of wearing face masks on whether face masks were mandatory in certain public areas during the strictest lockdown and found a strong positive response. On average, mandatory wearing of face masks leads to a 0.75 scale point increase in the change of the likelihood of wearing face masks during lockdown compared to before Corona, controlling for lockdown lengths and individual characteristics (p<0.01, see Table A.5 in Appendix A.2.1). The result does not change qualitatively when we control for other reported lockdown interventions. Thus, it seems that the lockdown strictness, especially the implementation of mandatory mask wearing, plays a major role in transforming short-term attitudes and behavior of wearing face masks. One potential explanation for the efficacy of mask mandates and lockdown measures in shaping habits is their ability to convey strong signals to the public about the necessity of behavioral change

(Bandyopadhyay et al., 2021). As widespread public mask-wearing is most effective in reducing viral transmission under conditions of high compliance (Howard et al., 2021), implementing mandatory mask policies may be especially advantageous in regions where mask-wearing during illness is not culturally normative.

As a robustness check, we run linear regression models with country dummy variables (i. e., fixed effects). The results are consistent with linear random-effect models. Both approaches show that greater lockdown strictness and mandatory face masks lead to a higher increase in the acceptance of wearing face masks during lockdowns compared to before Corona. Thus, the results are not driven by a single country.

Long-term Analysis The change in acceptance towards face masks seems to be long lasting. More than half of the respondents from countries other than Sweden remain open to wearing face masks when feeling sick after Corona, which might indicate a totally new norm in the post-Corona era (see Figure A.1 in Appendix A.1.2). The long-term change is measured by the difference of the expected likelihood rating of wearing face masks during illness after Corona and that before Corona. To estimate the long-term effects, we regressed the change in people's expectation after Corona compared to their responses before Corona, on lockdown strictness, lockdown lengths and individual characteristics. Data shows that the strictness of the lockdown and the length of the lockdown both contribute to the expected long-term change in the likelihood of wearing face masks in post-Corona times. As shown in Table 2.2 Column (1), one more self-reported governmental intervention leads to a 0.1 scale point increase in the change in the likelihood of wearing face masks when feeling sick after Corona compared to before Corona (p<0.01). Participants who reported a lockdown up to twenty weeks changed their likelihood of wearing face masks more than those who did not experience lockdown, controlling for individual characteristics (p<0.01 for all cases). Our results demonstrate that governmental policies during lockdowns play a crucial role in reshaping people's habit of wearing face masks during illness in the long run. This change can be of significant benefit for society and businesses as as a whole as face masks could effectively reduce the transmissions of not only the coronavirus but also other infectious diseases such as seasonal flu (Leung et al., 2020).

Table 2.1: Change in the likelihood of wearing face masks when feeling sick during lockdowns vs before Corona

	(1)	(2)	(3)	(4)
Number of bans	0.12***		0.10***	
	(0.01)		(0.01)	
Lockdown length:				
1-5 weeks		0.48***		0.70***
		(0.09)		(0.08)
6-10 weeks		0.34***		0.53***
		(0.09)		(0.08)
11-15 weeks		0.22**		0.40***
		(0.09)		(0.08)
16-20 weeks		−0.10		0.14
		(0.10)		(0.09)
more than 20 weeks		−0.40***		−0.14
		(0.11)		(0.09)
unknown		−0.07		0.06
		(0.10)		(0.10)
Age			0.02***	0.02***
			(0.00)	(0.00)
Female			0.16***	0.20***
			(0.03)	(0.03)
Married			0.06	0.08**
			(0.04)	(0.04)
College-level education or higher			−0.03	0.01
			(0.04)	(0.04)
Employed			0.08**	0.02
			(0.04)	(0.04)
Self-employed			−0.34***	−0.37***
			(0.06)	(0.06)
Student			0.36***	0.31***
			(0.07)	(0.07)
Household size			−0.03**	−0.02
			(0.01)	(0.01)
Risk attitude in general			0.00	0.01
			(0.02)	(0.02)
Risk attitude in health issues			−0.33***	−0.33***
			(0.02)	(0.02)
Financial stress during lockdown			0.15***	0.19***
			(0.02)	(0.02)
Health status			−0.03*	0.00
			(0.02)	(0.02)
Live with kids age 0-6			−0.16***	−0.16***
			(0.05)	(0.05)
Live with kids age 7-18			−0.16***	−0.17***
			(0.04)	(0.04)
Live with elderly above 65			0.08	0.13**
			(0.05)	(0.05)
Constant	1.39***	1.79***	0.57***	0.62***
	(0.17)	(0.35)	(0.09)	(0.11)
Country-specific effects	Yes	Yes	Yes	Yes
Observations	17,728	17,728	17,728	17,728
R^2	0.0218	0.0157	0.0729	0.0662

This table shows the random-effect models on the change of the likelihood of wearing face masks in time of illness during lockdowns compared to before Corona, as a function of lockdown strictness (measured as the number of self-reported bans during COVID-19 pandemic, the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. Standard errors in parentheses. *p < 0.1; **p < 0.05, ***p < 0.01

Table 2.2: Expected Change in the likelihood of wearing face masks when feeling sick after Corona vs before Corona.

	(1)	(2)	(3)	(4)
Number of bans	0.10***		0.09***	
	(0.00)		(0.00)	
Lockdown length:				
1-5 weeks		0.41***		0.66***
		(0.08)		(0.07)
6-10 weeks		0.36***		0.62***
		(0.08)		(0.07)
11-15 weeks		0.27***		0.57***
		(0.08)		(0.07)
16-20 weeks		0.05		0.37***
		(0.09)		(0.08)
more than 20 weeks		−0.23**		0.11
		(0.09)		(0.08)
unknown		−0.08		0.13
		(0.09)		(0.09)
Age			0.01***	0.01***
			(0.00)	(0.00)
Female			0.19***	0.22***
			(0.03)	(0.03)
Married			0.05	0.07**
			(0.03)	(0.03)
College-level education or higher			0.07**	0.09***
			(0.03)	(0.03)
Employed			0.08**	0.03
			(0.03)	(0.03)
Self-employed			−0.20***	−0.23***
			(0.05)	(0.05)
Student			0.22***	0.19***
			(0.06)	(0.06)
Household size			−0.02	0.00
			(0.01)	(0.01)
Risk attitude in general			−0.03*	−0.03
			(0.02)	(0.02)
Risk attitude in health issues			−0.23***	−0.24***
			(0.02)	(0.02)
Financial stress during lockdown			0.13***	0.17***
			(0.02)	(0.02)
Health status			0.01	0.03**
			(0.02)	(0.02)
Live with kids age 0-6			−0.07	−0.06
			(0.04)	(0.04)
Live with kids age 7-18			−0.10***	−0.11***
			(0.04)	(0.04)
Live with elderly above 65			0.05	0.08*
			(0.05)	(0.05)
Constant	1.00***	1.27***	0.34***	0.25**
	(0.13)	(0.25)	(0.08)	(0.10)
Country-specific effects	Yes	Yes	Yes	Yes
Observations	17,728	17,728	17,728	17,728
R^2	0.0241	0.0121	0.0568	0.0478

This table shows the random-effect models on the expected change of the likelihood of wearing face masks in time of illness after Corona compared to before Corona, as a function of lockdown strictness (measured as the number of self-reported bans during COVID-19 pandemic, the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. Standard errors in parentheses. *p < 0.1; **p < 0.05, ***p < 0.01

Sociodemographic Factors The change in habit of wearing face masks also varies by demographics. As shown in the 3rd and 4th columns of Table 2.1 and Table 2.2, the increase in the likelihood of wearing face masks during and after Corona increases with age with an estimate of 0.01 to 0.02 scale points per year in age (p<0.01 in the short-run and the long-run analysis), which is consistent with the fact that older people are at higher risks from COVID-19 and might be more willing to wear masks to protect themselves. Respondents living with elderly aged above 65 also reported a higher increase in the likelihood of wearing face masks than those who do not live with older people elderly during lockdowns, controlling for reported lockdown length (p<0.01 in the short-run analysis and p<0.05 in the long-run analysis). On the other hand, the change in the likelihood of wearing face masks during lockdowns compared to before Corona is lower for people living with young children than those without children at home (p<0.01). Facial expressions may be specifically important when communicating with kids and might be physically exhausting while being active with the kids, making masks less attractive. Our data also shows that females changed their acceptance of face masks more than males both in the short run and in the long run. On average, females increased the likelihood of wearing face masks more than males by a range of 0.16 to 0.22 scale point depending on the model both during lockdown and after Corona (p<0.01 in all cases).

Employment situation also affects the change in behavior. Those who are employed expect to increase the likelihood of wearing face masks more than the unemployed or the retired ones after Corona compared to before the pandemic, controlling for other individual characteristics (see Table 2.2 Column (3), p<0.05). On the other hand, self-employed individuals tend to change their likelihood of wearing face masks less compared to the other groups (p<0.01). This might be because self-employed individuals often work at home or alone and thus do not need to wear a mask. The increase in the likelihood of wearing face masks is higher among students than the unemployed and the retired. Again, this could be because many universities imposed mask wearing.

As could be expected, a higher willingness to take risks in health issues leads to a lower increase in the likelihood of wearing face masks in time of illness both during lockdowns and after Corona (p<0.01). On average, with an increase of one standard deviation in the willingness to take risks in health issues, people lower the change in the likelihood of wearing face masks by 0.33 and 0.24 scale points in the before-during comparison and the before-after comparison, respectively (p<0.01). This result is consistent with previous findings that risk tolerance is positively correlated with unhealthy behaviors such as smoking and heavy drinking (Anderson and Mellor, 2008; Dave and Saffer, 2008) and negatively correlated with compliance with social distancing during the COVID-19 pandemic (Müller and Rau, 2021). To motivate people with high risk-taking tendency in health issues, it might be helpful for media and governments to emphasize the social costs of breaking hygienic rules and other interventions. People might be less prone to take risky actions if they know that these actions not only affect themselves but can also have might also have a negative consequence on other people (Campos-Mercade et al., 2021).

People's responses to the pandemic may also be influenced by their political preferences (Allcott et al., 2020; Barrios and Hochberg, 2020; Grossman et al., 2020; Serra-Garcia and Szech, 2020). For instance, regions with a higher share of Trump supporters are associated with lower risk perceptions during the COVID-19 pandemic. Further, Trump supporters engaged in less social distancing (Barrios and Hochberg, 2020) and demonstrate lower demand for antibody tests (Serra-Garcia and Szech, 2020). To estimate the effect of political preferences on the change in people's likelihood of wearing face masks, we asked respondents to rate how much they liked Trump's approach to COVID-19 crisis from 1 (extremely dislike) to 7 (extremely like). We received responses from 15,694 participants on this question. Consistent with previous findings, regression results show that participants who are more fond of Trump exhibit a lower increase in the likelihood of wearing face masks compared to those who are more against Trump's approach (see Table 2.3). This result is robust in both the short-run change and the expected long-run change.

Table 2.3: The effects of political preferences on the change of wearing face masks when feeling sick

	(1) Short Run	(2) Short Run	(3) Long Run	(4) Long Run
Approval rating for Trump's approach to COVID	-0.43^{***}	-0.44^{***}	-0.30^{***}	-0.32^{***}
	(0.02)	(0.02)	(0.02)	(0.02)
Number of bans	0.08^{***}		0.08^{***}	
	(0.01)		(0.01)	
Lockdown length:				
1-5 weeks		0.65^{***}		0.65^{***}
		(0.09)		(0.08)
6-10 weeks		0.56^{***}		0.66^{***}
		(0.09)		(0.07)
11-15 weeks		0.45^{***}		0.62^{***}
		(0.09)		(0.08)
16-20 weeks		0.19^{*}		0.42^{***}
		(0.10)		(0.09)
More than 20 weeks		-0.03		0.22^{**}
		(0.10)		(0.09)
Unknown		0.126		0.20^{*}
		(0.10)		(0.09)
Constant	0.61^{***}	0.56^{***}	0.35^{***}	0.17
	(0.10)	(0.12)	(0.09)	(0.11)
Demographic controls	Yes	Yes	Yes	Yes
Country-specific effects	Yes	Yes	Yes	Yes
Observations	15694	15694	15694	15694
R^2	0.1062	0.1030	0.0792	0.0742

This table shows the random-effect models on the change of the likelihood of wearing face masks during sickness, as a function of individual's approval of Trump's approach to dealing with the COVID-19 crisis. Columns 1-2 represent short-run change, and columns 3-4 represent long-run change. All regressions include age, gender, marital status, education level, employment status, financial stress level during lockdowns, risk attitude in general, risk attitude in health related issues, perceived health status, whether there are kids at home and whether there are elderly aged above 65 at home as controls. Approval rating for Trump's approach, risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized. Standard errors in parentheses. *p < 0.1; **p < 0.05, ***p < 0.01

Hand Washing

Our data shows that a new hand hygiene habit is likely to be formed as a response to the pandemic. On average, the reported frequency of daily hand washing increased by 43.59% during lockdowns. Participants expect an increase by 30.77% after Corona, compared to the level before Corona. Figure 2.3 illustrates the absolute change and the percentage change in daily hand washing frequency by region. As the figure shows, people reported that they washed their hands much more frequently during lockdowns compared to before Corona. Though people expected to wash their hands less often after Corona compared to during lockdowns, the expected level in the post-Corona time is still significantly higher than that before Corona (p<0.001, two-sided t-test, n = 17,728), which indicates a transition to an improved hygienic habit in the long run. This result is robust across different regions.

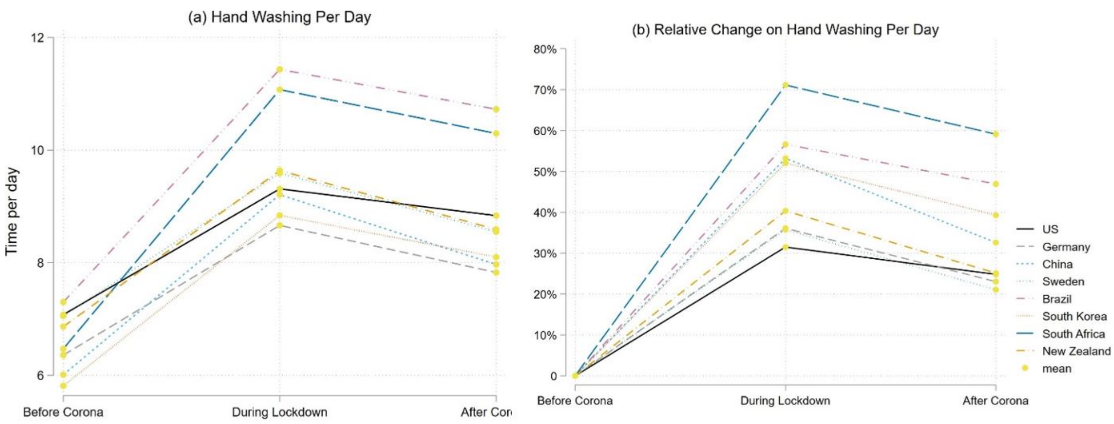


Figure 2.3: Daily hand washing frequency. The figure exhibits the absolute change (left panel) and the percentage change (right panel) of the frequency of hand washing per day by time period and country.

To estimate the short-run effects of lockdowns on the change of hand washing habits, we regress the change in the reported daily hand washing frequency during lockdown and that before Corona on lockdown strictness and self-reported lockdown length separately and then control for individual characteristics. The long-run change is measured by the difference in the expected daily hand washing frequency after Corona and that before Corona.

An increase in the lockdown strictness leads to a higher increase in the frequency of hand washing per day both in the short run and in the long run. As shown in Table 2.4 Column (1), one more self-reported governmental intervention leads to a 0.2 increase in the change of daily hand washing frequency during the pandemic compared to before Corona (p<0.01). In other words, on average, people who reported experiencing 5 lockdown measures are expected to increase the frequency of hand washing per day by almost one more than those who reported experiencing no lockdown measures, controlling for country random effects. Table 2.5 presents the regression results for the before-after comparison. It shows that with every reported lockdown intervention experienced, the change in the expected hand washing frequency per day increases by 0.14 times ($p < 0.01$). This indicates that people from regions with stricter lockdowns expect that they are more likely to stick with the habit of frequent hand washing after the pandemic. Data also shows that lockdown length also plays a significant role in reshaping the hand hygiene habit especially in the first 15 weeks of lockdown ($p < 0.01$, see Columns 2 of Table 2.4 and Table 2.5).

The change of hand hygiene habit is also affected by sociodemographic factors (see Columns 3 and 4 of Table 2.4 and Table 2.5). For instance, people of higher age reported a higher increase in the frequency of hand washing per day more than younger respondents both during lockdowns and in expectation after Corona ($p < 0.01$). Those who live with kids at home also reported a higher increase in hand washing time per day compared to those who live without a kid, controlling for other factors. However, the change in the reported behavior does not differ significantly between those who live with elderly and those who do not, controlling for lockdown strictness. Household size is positively associated with the change in hand hygiene habit ($p < 0.01$). In addition, there is a greater change among females than males ($p < 0.01$). On average, females increase the hand washing frequency more than males by 0.23 time per day during lockdowns and 0.19 time per day in expectation after Corona, controlling for lockdown strictness ($p < 0.01$). A higher willingness to take risks in health issues is also associated with a smaller change in hand washing frequency per day ($p < 0.01$). This result is consistent with the finding on the change of wearing face masks.

Relative to the unemployed and the retired individuals, those who are self-employed exhibit a significant smaller change of hand hygiene habit both during lockdowns and in expectation after Corona ($p < 0.01$). The difference in the change of hand washing frequency is statistically insignificant between domestic workers and the unemployed or the retired. Students reported a higher increase in daily hand washing during lockdowns compared to before Corona ($p < 0.01$). However, the change is not statistically different in expectation after Corona between students and the unemployed or the retired.

Similar to the results of the change in the likelihood of wearing face masks, the increase in the frequency of hand washing per day decreases with individual's approval rating for Trump's approach to the COVID-19 crisis both in the short run and in the long run expectation ($p < 0.01$, see Table 2.6). This result is robust to different ethnicities in the US (see Appendix Figure A.5 and Appendix Figure A.6), which again suggests that Trump supporters may be less likely to engage in activities which could potentially protect themselves from COVID-19 infection (Barrios and Hochberg, 2020; Serra-Garcia and Szech, 2020).

Table 2.4: Change in the frequency of hand washing per day during lockdowns vs before Corona.

	(1)	(2)	(3)	(4)
Number of bans	0.20***		0.18***	
	(0.01)		(0.01)	
Lockdown length:				
1-5 weeks		0.50***		0.45***
		(0.15)		(0.13)
6-10 weeks		0.52***		0.43***
		(0.15)		(0.13)
11-15 weeks		0.60***		0.53***
		(0.15)		(0.13)
16-20 weeks		0.22		0.28*
		(0.16)		(0.15)
more than 20 weeks		−0.05		0.15
		(0.17)		(0.15)
unknown		−0.31*		−0.38**
		(0.16)		(0.16)
Age			0.02***	0.02***
			(0.00)	(0.00)
Female			0.23***	0.30***
			(0.05)	(0.05)
Married			0.11*	0.16**
			(0.06)	(0.06)
College-level education or higher			0.12**	0.15***
			(0.06)	(0.06)
Employed			0.09	0.00
			(0.06)	(0.06)
Self-employed			−0.59***	−0.69***
			(0.10)	(0.10)
Student			0.36***	0.32***
			(0.12)	(0.12)
Household size			0.06***	0.10***
			(0.02)	(0.02)
Risk attitude in general			0.02	0.05
			(0.03)	(0.03)
Risk attitude in health issues			−0.24***	−0.27***
			(0.03)	(0.03)
Financial stress during lockdown			0.45***	0.50***
			(0.03)	(0.03)
Health status			0.09***	0.14***
			(0.03)	(0.03)
Live with kids age 0-6			0.14*	0.16**
			(0.07)	(0.08)
Live with kids age 7-18			0.18***	0.15**
			(0.06)	(0.07)
Live with elderly above 65			0.11	0.14*
			(0.08)	(0.08)
Constant	2.08***	2.74***	0.62***	1.07***
	(0.27)	(0.40)	(0.14)	(0.18)
Country-specific effects	Yes	Yes	Yes	Yes
Observations	17,728	17,728	17,728	17,728
R^2	0.0376	0.0058	0.0640	0.0422

This table shows the random-effect models on the change of the frequency of hand washing per day during lockdowns compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. Standard errors are reported in parentheses. *p < 0.1; **p < 0.05, ***p < 0.01

Table 2.5: Change in the frequency of hand washing per day in expectation after Corona vs before Corona

	(1)	(2)	(3)	(4)
Number of bans	0.14***		0.13***	
	(0.01)		(0.01)	
Lockdown length:				
1-5 weeks		0.42***		0.40***
		(0.12)		(0.11)
6-10 weeks		0.38***		0.32***
		(0.12)		(0.11)
11-15 weeks		0.50***		0.51***
		(0.12)		(0.11)
16-20 weeks		0.28**		0.33***
		(0.13)		(0.12)
more than 20 weeks		0.25*		0.36***
		(0.14)		(0.13)
unknown		−0.32**		−0.31**
		(0.13)		(0.13)
Age			0.01***	0.01***
			(0.00)	(0.00)
Female			0.19***	0.24***
			(0.04)	(0.04)
Married			−0.01	0.02
			(0.05)	(0.05)
College-level education or higher			0.04	0.06
			(0.05)	(0.05)
Employed			0.03	−0.03
			(0.05)	(0.05)
Self-employed			−0.29***	−0.38***
			(0.08)	(0.08)
Student			0.15	0.14
			(0.10)	(0.10)
Household size			0.06***	0.09***
			(0.02)	(0.02)
Risk attitude in general			−0.09***	−0.06**
			(0.03)	(0.03)
Risk attitude in health issues			−0.08***	−0.11***
			(0.03)	(0.03)
Financial stress during lockdown			0.35***	0.39***
			(0.02)	(0.02)
Health status			0.13***	0.16***
			(0.02)	(0.02)
Live with kids age 0-6			0.20***	0.21***
			(0.06)	(0.06)
Live with kids age 7-18			0.13**	0.11**
			(0.05)	(0.05)
Live with elderly above 65			0.00	0.02
			(0.07)	(0.07)
Constant	1.52***	1.94***	0.51***	0.75***
	(0.29)	(0.40)	(0.12)	(0.15)
Observations	17,728	17,728	17,728	17,728
R^2	0.0280	0.0061	0.0486	0.0339

This table shows the random-effect models on the expected change of the frequency of hand washing per day in expectation after Corona compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. Standard errors are reported in parentheses. *p < 0.1; **p < 0.05, ***p < 0.01

Table 2.6: The effects of political preferences on the change of daily hand washing frequency

	(1) Short Run	(2) Short Run	(3) Long Run	(4) Long Run
Approval rating for Trump's approach to COVID	-0.66^{***}	-0.72^{***}	-0.66^{***}	-0.72^{***}
	(0.03)	(0.03)	(0.03)	(0.03)
Number of bans	0.08^{***}		0.08^{***}	
	(0.01)		(0.01)	
Lockdown length:				
1-5 weeks		0.35^{*}		0.35^{*}
		(0.14)		(0.14)
6-10 weeks		0.38^{**}		0.38^{**}
		(0.13)		(0.13)
11-15 weeks		0.58^{***}		0.58^{***}
		(0.14)		(0.14)
16-20 weeks		0.191^{*}		0.42^{***}
		(0.10)		(0.09)
More than 20 weeks		-0.03		0.22^{**}
		(0.10)		(0.09)
Unknown		0.13		0.20^{*}
		(0.10)		(0.09)
Constant	0.61^{***}	0.56^{***}	0.35^{***}	0.17
	(0.10)	(0.12)	(0.09)	(0.11)
Demographic controls	Yes	Yes	Yes	Yes
Observations	15694	15694	15694	15694
R^2	0.1062	0.1030	0.0792	0.0742

This table shows the random-effect models on the change of daily hand washing frequency, as a function of individual's approval of Trump's approach to dealing with the COVID-19 crisis. Columns 1-2 represent short-run change, and columns 3-4 represent long-run change. All regressions include age, gender, marital status, education level, employment status, financial stress level during lockdowns, risk attitude in general, risk attitude in health related issues, perceived health status, whether there are kids at home and whether there are elderly aged above 65 at home as controls. Approval rating for Trump's approach, Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized. Standard errors in parentheses. *p < 0.1; **p < 0.05, ***p < 0.01

2.4.2 Twitter and Google Trends

Analysis of tweets

Consistent with the survey data, we find an upward trend in the share of tweets referring to wearing masks and hand washing on Twitter (see Figure 2.4). At its peak in early March 2020 (i.e., when the pandemic reached the U.S.), the share of tweets referring to hand washing was 12.9 times higher than at the beginning of our observation period in end of January 2020. Thereafter, there was a gradual shift in the share of tweets from hand washing towards wearing masks. After June 2020, the average share of tweets referring to hand washing returned almost back to the level from before the pandemic. This might be explained by the established habit of more frequent hand washing. In contrast, we see an even higher share of tweets referring to face masks during the last months of our observation period (i.e., after the stay-at-home period has ended). At its peak in the end of June 2020, Twitter users posted 15.6 times more about wearing masks than at the beginning of our observation period.

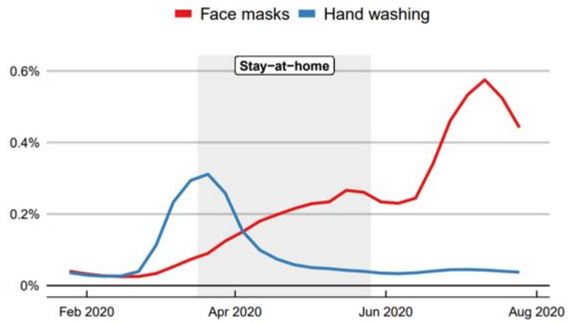


Figure 2.4: Hygiene habits on Twitter. Shown is the average share of tweets referring to "Face Masks" and "Washing Hands" within four U.S. states (California, Florida, New York and Texas. Results are based on approximately 9.4 million Tweets. Stay-at-home order effective: CA 2020/03/19; NY 2020/03/22; TX 2020/04/02; FL 2020/04/03.)

We also compared the frequency of tweets reacting to hygiene habits to digital habits that have changed as well during the pandemic (see Figure 2.5). We find that users tweet extensively about digital habits such as teleworking, video conferencing, and digital gaming and that these digital habits have experienced significant gains in popularity on Twitter during the pandemic. However, we observe the relatively strongest and most long-lasting change for tweets referring to mask wearing. We also find similar patterns for digital habits in our survey data (see Figure 2.6 and Figure 2.7). There was significant increase in the amount of time people spent on digital activities such as teleworking, video conferencing and digital gaming. However, the change in hygiene habits is stronger and people expect to stick with hygiene habits more than the digital habits after the pandemic.

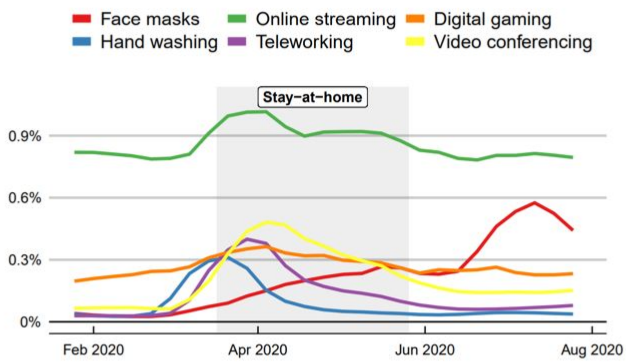


Figure 2.5: Comparison of hygiene habits and digital habits on Twitter. Shown is the average share of tweets referring to habits within four U.S. states (California, Florida, New York and Texas). Results are based on approximately 9.4 million Tweets. Stay-at-home order effective: CA 2020/03/19; NY 2020/03/22; TX 2020/04/02; FL 2020/04/03.)

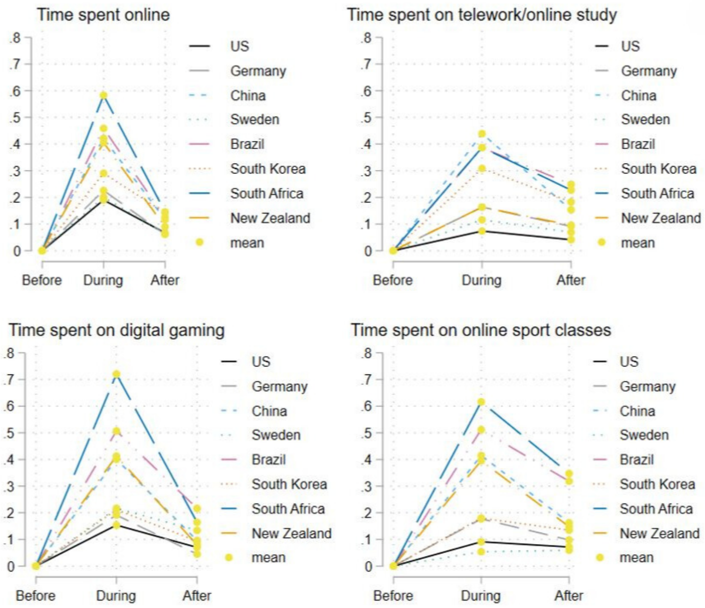


Figure 2.6: Change of the time spent on digital activities per day (survey data-1)

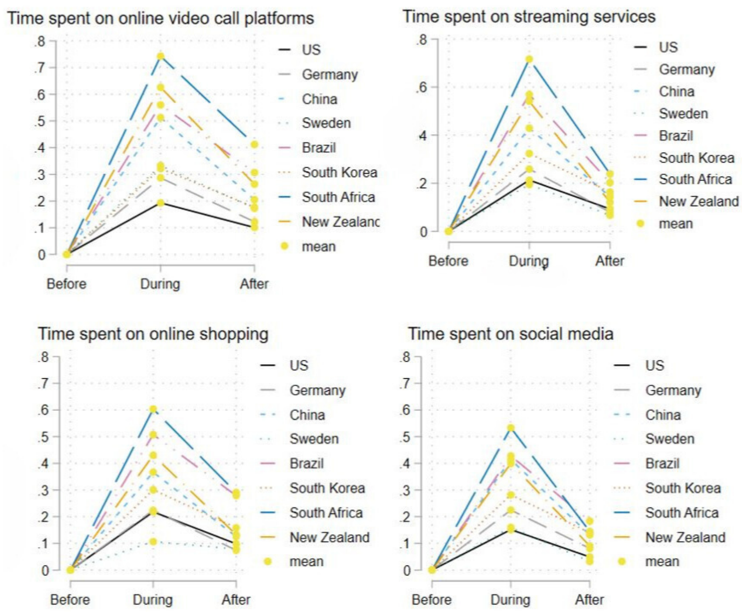


Figure 2.7: Change of the time spent on digital activities per day (survey data-2)

Google Trends

Figure 2.8 shows the search query volumes of keywords related to hygiene habits on Google Trends. We find substantial changes in the search volume for both mask wearing and hand washing. Consistent with our analysis of social media posts from Twitter, there is an early upward trend for hand washing in March 2020, i.e., when the pandemic reached the U.S. Thereafter, we again observe a shift from hand washing towards wearing face masks. The search volume index for face masks peaked during the stay-at-home period in April 2020. Notably, the increased search interest in hand washing and wearing masks seems to be long-lasting: compared to the beginning of our observation period, the weekly search query volumes after the stay-at-home period has ended were 19.1 times higher for mask wearing and 6.9 times higher for hand washing.

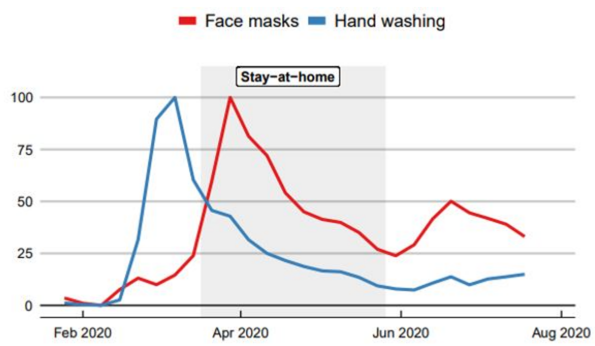


Figure 2.8: Hygiene habits on Google Trends. Shown in Google Trends' search volume index for "Face Masks" and "Washing Hands" within four U.S. states (California, Florida, New York and Texas). Results are based on approximately 9.4 million Tweets. Stay-at-home order effective: CA 2020/03/19; NY 2020/03/22; TX 2020/04/02; FL 2020/04/03.

2.5 Discussion

This study investigates the formation and long-term belief of hygienic habit change during the COVID-19 pandemic, highlighting the influence of lockdown stringency and government interventions on behavioral change. Our findings reveal a marked improvement in hygiene practices, such as mask wearing and hand washing, during lockdown periods. Furthermore, survey results indicate that individuals expect to maintain these improved habits to a significant degree after the pandemic.

2.5.1 Habit Formation and the Role of Policy Enforcement

The study highlights the importance of governmental mandates in fostering fast adoption of hygiene practices. Our results suggest that enforced measures, such as mask mandates, are more effective than mere recommendations in driving both initial compliance and long-term belief of hygienic behavior. The persistence of long-term belief of habit change and increased hygiene-related search queries, even after the easing of lockdown measures, indicates potential for these behaviors to become new societal norms. However, our analysis also suggests that prolonged lockdowns could potentially diminish long-term adherence. Behavioral fatigue may reduce compliance over time, highlighting the importance of balancing the strictness and duration of interventions to sustain public cooperation. These findings provide insights for policymakers designing interventions to manage future public health crises or encourage pro-social behavior in other domains.

The integration of survey data with social media and Google Trends analysis strengthens the robustness of our findings. This multi-source approach mitigates potential biases associated with self-reported data (Fung and Cairncross, 2007), offering a more comprehensive view of behavioral trends. The significant correlations between survey responses, tweet frequencies, and search query volumes provide strong external validation for our conclusions.

2.5.2 Demographic Variation in Behavior Changes

The adoption of hygienic habits, including face mask usage and hand-washing, exhibited notable demographic variation. For example, older individuals reported a greater increase in both mask-wearing and hand-washing frequency compared to younger respondents, both during lockdowns and in expectation of the post-pandemic period. This is likely due to the higher perceived health risks associated with COVID-19 among older populations (Team, 2020). Similarly, individuals living with children at home showed a greater increase in hand-washing frequency than those without children, while the change in mask-wearing behavior was also higher among this group. This may reflect an increased emphasis on hygiene to protect children, even though the change in mask-wearing was less pronounced for those with young children, potentially due to the need for facial expression in communication and physical discomfort when interacting with children.

In terms of gender, females exhibited a larger increase in both mask-wearing and hand-washing frequency compared to males, both during lockdowns and in the post-pandemic period. Household size also played a role, with larger households reporting a more substantial change in hand hygiene behavior. Interestingly, individuals who lived with elderly family members did not report a significantly different change in hand-washing behaviors compared to those who did not, after controlling for lockdown strictness. Employment status had a similar influence on both behaviors. Self-employed individuals reported a significantly smaller change in both hand-washing and mask-wearing habits compared to the employed, likely due to lower exposure to public environments. Students, on the other hand, showed a higher increase in hand-washing frequency during lockdowns, possibly influenced by institutional mandates. However, this difference was not significant when considering expectations after the pandemic.

As expected, risk tolerance in health-related behaviors was inversely related to changes in both mask-wearing and hand-washing frequency. Those with a higher willingness to take health risks showed a smaller increase in these hygienic behaviors, reflecting a broader tendency for risk-tolerant individuals to engage less in preventive health actions. These findings underline the complexity of demographic factors influencing hygienic habit formation and suggest the importance of targeted public health messaging that considers these factors.

2.5.3 Implications for Businesses and Public Health

The findings carry significant implications for industries, particularly in the hospitality and service sectors. Maintaining rigorous hygiene standards has become a critical factor in consumer satisfaction, as people increasingly prioritize cleanliness in their decision-making (Yang et al., 2024; Pereira et al., 2023). Businesses that adapt to these heightened expectations are more likely to thrive in a post-pandemic environment. In this context, companies should not only implement hygiene measures but also actively communicate these efforts to consumers, reinforcing their commitment to safety and public health. For public health officials, these insights highlight the necessity of clear, consistent, and enforceable policies to ensure both short-term uptake and long-term sustainability of beneficial health behaviors.

2.5.4 Future Research Directions: Persistence of Pandemic-Induced Habits

A key direction for future research is to explore the persistence of the new hygienic habits formed during the COVID-19 pandemic. While our analysis focuses on the initial stages of hygienic habit formation and individuals' long-term beliefs about behavioral change, whether people stick with the new habits after the pandemic remains an open question. Although persistent beliefs in long-term behavioral change after lockdowns may be widespread, they do not necessarily translate into real changes in behavior. For example, using longitudinal data, Brüggemann and Olbrich (2023) reported that 10.37% of the consumers in Germany avoided shopping at brick-and-motor stores during the pandemic lockdown and nearly all observed consumers visited physical stores again once the lockdown ended. This suggests that the pandemic restrictions did not lead to a permanent shift from offline to online shopping channels. Gueron-Sela et al. (2023) observed an increase in children's screen time and exposure to background television during the COVID-19 lockdowns compared to the pre-lockdown period, which are positively correlated with the children's behavioral problem. However, they found no evidence linking these changes in screen media exposure to children's behavioral problems in the post-lockdown phase.

On the other hand, some research shows a lasting impact of lockdowns on physical activities. Donizzetti (2023) reported an increase in self-reported physical activity levels during the lockdowns relative to pre-pandemic levels. While a slight decline in physical activity was observed two years after the initial survey, the difference compared to lockdown periods was not statistically significant, suggesting a modest yet positive long-term impact on physical activity. Despite the limited and mixed results on the long-term impact of Corona lockdowns on behavioral change, hygienic habits might be enduring. For instance, we continue to observe the use of disinfectants and hand sanitizers in public places such as restaurants and at the doctor's offices after the Corona lockdowns, where these practices were sometimes absent before the pandemic. These findings highlight the complexity of assessing whether pandemic-induced behavioral changes are sustained over time. Future research could explore these dynamics using observational data or experimental designs to isolate causal effects more precisely.

2.6 Conclusion

In this chapter, we study habit formation during the Corona crisis as well as long-time expectations for when the pandemic is over. There was an improvement in hygiene behavior during lockdowns compared to that before the Corona outbreak. People also expect to stick with the improved hygienic habits to a large extent after the pandemic, though lengthy lockdown might backfire. This change in hygienic behavior seems to be highly driven by the strictness of the lockdowns and governmental interventions. Hence, enforcing, instead of only recommending, a new hygiene habit like mask wearing increases short-term uptake, but also long-time belief on hygiene habits. For businesses, our results suggest that maintaining good hygiene standards is becoming more and more important to strive, especially for those in the hospitality sector, as people care more about hygiene both during and in the aftermath of the pandemic.

One limitation of our survey is that it relies on self-reported data. Furthermore, participants might be subject to recall bias and might over-report socially desirable responses (Fung and Cairncross, 2007). However, the upward trend of hygiene behavior in survey data is supported by analyses of social media, i.e., Twitter. There is a drastic increase in the proportion of tweets for face masks and washing hands during the first wave of the pandemic, and the upward trend for face masks is more long-lasting. If they choose to tweet about hygiene or other habits, this shows that they engage in these topics. Furthermore, we analyzed data from Google Trends, confirming our findings that interest in hygiene habits significantly changed during the Corona pandemic.

3 Digital Habit Change during the COVID-19 Lockdowns

The previous chapter focuses on how hygiene habits, namely mask-wearing during sickness and handwashing frequency, changed during the Corona lockdowns, as well as people's long-term expectation on whether they will stick to these changes in post-Corona time. Building on this, the current chapter aims to give insights on another key change that brought about by the pandemic: digital habits. Specifically, it investigates changes in the amount of time individuals spent online across various activities, including general internet use, streaming services, teleworking and online studying, video conferencing platforms, and digital gaming.

3.1 Introduction

In March 2020, the COVID-19 outbreak was declared as a global pandemic by the World Health Organization, and more than 777 million COVID-19 confirmed cases have been reported as of May 2025 (World Health Organization, 2025). In response to the pandemic, many countries have implemented different degrees of lockdown to limit the spread of the virus, from social distancing to stay-at-home order. Closure of shopping malls and schools was also enforced in several countries during the early waves of the pandemic. These lockdown measures have triggered an inevitable shift in how people live their lives in many countries, not only in terms of how they work, but also how they spend leisure time. One major change in lifestyle during the pandemic was more time spent online (Trott et al., 2022). People had to switch to online social network platforms to stay in touch with family and friends (Cmentowski and Krüger, 2020). Business meetings, education, academic conferences were also forced to shift online during the

[0] This chapter is joint work with Jella Pfeiffer, Nicolas Pröllochs and Nora Szech.

lockdown period (Mheidly et al., 2020). There was a higher demand for teleworking, online studying, e-commerce and digital entertainment such as streaming services and online gaming (Feldmann et al., 2020). Platforms such as Zoom, Teams and WhatsApp quickly evolved into essential tools for both work and social interaction.

As has been previously reported in the literature, there was a surge in online activities during the Corona pandemic (Feldmann et al., 2020; Claesdotter-Knutsson et al., 2022; Nagata et al., 2022). Lockdown measures have led to a significant increase in internet traffic demand (Feldmann et al., 2020) and the use of digital platforms for online working and online studying. Pandey et al. (2020) provide an overall discussion of how COVID-19 drove a digital transformation in both public and private life, which includes increased use of telemedicine, digital payments, and online learning. Their work discusses the potential persistence of these changes in the long run with a focus on institutional adoption. Using a nationwide survey in Greece, Mouratidis and Papagiannakis (2021) observed a shift from physical participation in activities to online activities during the pandemic. They found that both the the frequency and the perceived importance of online activities such as teleworking, teleconferencing, and online learning increased due to the pandemic.

The psychological impact and emotional effects of the Corona pandemic has been investigated in previous literature. Several studies report that excessive use of the Internet and social media during Corona lockdowns was associated with increased anxiety, loneliness, and even addictive behaviors (Dong et al., 2020; Chen et al., 2021). These findings are consistent in studies of screen time among children and adolescents. Nagata et al. (2022) report that recreational screen time among adolescents doubled to approximately 7.7 hours per day in early lockdown in the US. Teng et al. (2021). Cmentowski and Krüger (2020) looked into online gaming behaviors among adolescents and found a significant increase in the time spent on video games during lockdown. Though increased online gaming carried a potential mental health risk, multiplayer gaming served as an important substitute of face-to-face social interaction during periods of lockdown (Cmentowski and Krüger, 2020). While some studies suggest that excessive internet use may exacerbate mental health issues (Dong et al., 2020), others argue that it can offer emotional support and function as a coping mechanism for loneliness and distress during prolonged isolation (Boursier et al., 2020).

In the domain of digital communication, Nguyen et al. (2020) found a substantial increase in the use of online platforms such as Zoom and Skype for both work and social interaction. Their findings suggest that digital communication did not simply replace in-person interaction in the short run, but also changed social norms regarding availability and intimacy.

Several studies highlight changes in consumer behavior, such as the surge in online food shopping (Chang and Meyerhoefer, 2021) and streaming service use (Lemenager et al., 2021), reinforcing the notion of digital environments as new habit-forming spaces during lockdowns. However, these studies tend to focus on specific platforms or consumer decisions, without considering broader, integrated patterns of digital habit change across multiple life domains.

While previous literature documents increased digital activity during the pandemic, three main gaps remain. First, most studies use country-specific dataset and do not compare behavioral changes across regions with different lockdown policies. The role of lockdown strictness and duration is underexplored in explaining changes in behavior. Second, they often examine a single type of digital activity in isolation. This may limit the insight into how various digital habits may have co-evolved. Third, few studies explore the long-term effect of lockdown on digital habit change and people's expectations about the future.

Our study contributes to the literature by addressing these limitations. We draw on a large, cross-national dataset covering eight countries and examine multiple digital habits—general time spent online, time spent on streaming, teleworking or online studying, video calling, and online gaming. By measuring the time spent on different digital activities before, during, and in expected after the pandemic, we offer a unique perspective on both short-term habit change and the potential for long-term behavioral shift. Furthermore, our study examines both policy-level factors (e.g., lockdown strictness and lockdown length) and individual characteristics to understand what drove habit change and what may determine its potential persistence.

3.2 Data and Empirical Strategy

The dataset that we used for this study is the same as that used for the previous study. The data collection for the survey commenced on June 15, 2020, and concluded on June 29, 2020. We gathered 17,728 observations for the survey with samples being representative in terms of age and gender distribution for the regions of interest, which includes California, Texas, Florida, New York State, USA as a whole, five regions in China (Wuhan City, other cities in Hubei Province, Henan Province, Guangdong Province, Beijing), South Korea, Germany, Sweden, New Zealand, Brazil and South Africa. In China, we have to focus on younger people because the survey is done online and the internet penetration rate among older people in China is low (Dynata, 2022). Details of the sample are shown in Appendix A.1.1. We chose these regions because there is a large variation in terms of how local governments responded to the pandemic, and the strictness of the lockdowns differed across regions. Moreover, our sample consists of participants from six different continents.

The survey assesses behavioral habits by examining the time spent on various activities across three distinct periods: before Corona, during the strictest lockdown, and people's expectation after Corona, that is, when the pandemic has ended. Specifically, (i) before Corona, (ii) during the strictest lockdown and (iii) after Corona were described as (i) the months leading up to the outbreaks, (ii) the period where participants experienced the strictest constraints, and (iii) a future time when Corona is no longer a pressing issue and life has returned to "normal". In this paper, we mainly focus on the change of habits with a specific focus on digital habits.

As a measurement of the strictness of the lockdown policies, we used the number of self-reported governmental interventions out of 11 listed restrictions during the strictest lockdown. These 11 interventions include: ban on dining in restaurants and bars, closure of shopping malls, ban on going to parks, ban on going outside for leisure reasons or sports, ban on traveling within the country for leisure reasons, mandatory temperature/health checks when leaving your accommodation, ban on religious gatherings, ban on gatherings at home (e.g. visits from family, friends, etc.), ban on going out except for essential reasons (e.g. groceries shopping, doctor's visit, work, etc.) and total ban on going outside. In addition, we test the effect of the length of the lockdown policies on habit change.

We estimate random-effect regression models to determine the effects of lockdowns on changes of habits both in the short run and in the long run. The short-run change of digital habits for each survey participant i in country c is measured by the difference between the time spent on an activity per day and that before Corona. The long-run change is measured by the difference in the time spent on the activity in expectation after Corona and that before Corona. We regress the change in the responses ($HabitChange_{i_c}$) on the strictness of the lockdown and the self-reported lockdown length[1] in two separate models to test the effect of lockdown on changes of habits. The strictness of the lockdown is measured by the number of self-reported governmental interventions out of 11 listed restrictions during the strictest lockdown (see Appendix A.4). In our regression models, we control for the following individual characteristics of each participant (X_i): age, gender, marital status, education level, employment status, household size, financial stress level during lockdowns, risk attitude in general, risk attitude in health-related issues, perceived health status, whether there are kids at home and whether there are elderly aged above 65 at home. In addition, we control for heterogeneity across countries through the use of country-specific random effects. The regressions take the following form:

$$HabitChange_{i_c} = \beta_0 + \beta_1 LockdownStrictness_i + \beta_3^T X_i + u_c \tag{3.1}$$

$$HabitChange_{i_c} = \beta_0 + \beta_2 LockdownLength_i + \beta_3^T X_i + u_c \tag{3.2}$$

with parameters $\beta_0, \ldots, \beta_3$ (out of which β_3 is a vector), and country-specific random effect u_c.

3.3 Results

3.3.1 Overall Trend on Time Spent Online

Effects of Lockdown

We ran two random-effect regression models to estimate the relationship between lockdown characteristics (i.e. the strictness and the length of lockdown), and changes in time spent on online activities. Each model sequentially adds controls to account for individual characteristics, socioeconomic factors, and psychological traits. We measured the changes in digital habits by asking the amount of time that participants spent on different online activities per day before

[1] The variable lockdown length is defined as 7 categories: 0 week, 1-5 weeks, 6-10 weeks, 11-15 weeks, 16-20 weeks, more than 20 weeks and unknown lockdown length, with 0 week (i.e. no lockdown) being the reference category.

Corona, during the strictest lockdown (if applicable), and in expectation after Corona. Table 3.1 and Table 3.2 each present four specifications. Model (1) and (2) include only lockdown-related variables; Model (3) and (4) add demographic controls, psychological and household variables.

Overall, there was a significant increase in the reported time spent online during lockdowns compared to before Corona and the result is robust to different regions. On average, the reported time spent online increased by 32.6% from before Corona to during lockdowns and by 9.5% in expectation after Corona compared to the level before Corona (n=17728, $p < 0.01$, two-sided t-test). Notably, the reported increase was higher among participants from South Africa and Brazil than those from other regions.

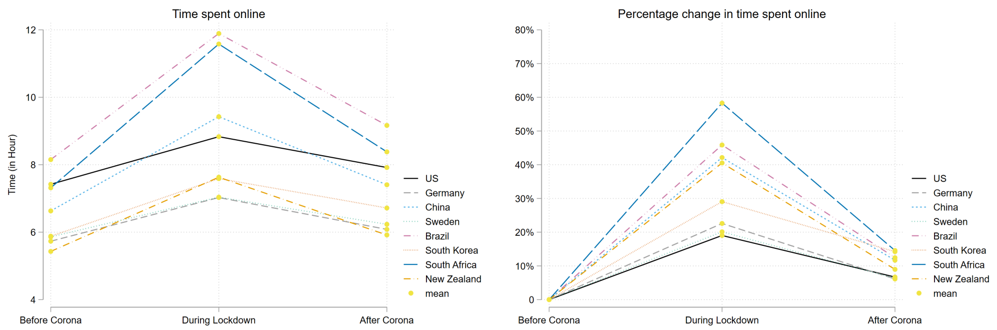


Figure 3.1: The figure exhibits the absolute change (left panel) and the percentage change (right panel) of time spent online per day by time period and country.

Across all specifications, the strictness of the lockdown and the lockdown length significantly affect the change in the total amount of time spent online per day. As shown in Table 3.1 Column (3), on average, one more self-reported COVID-19 intervention leads to a 0.19-hour increase in the change of the time spent online per day during lockdowns compared to before Corona, controlling for country random effects and individual characteristic factors ($p < 0.01$). In other words, those who reported 5 interventions on average increased the time spent online more than those who experienced no lockdown by approximately 1 hour. Lockdown length also plays a role, but the effect is not linear. As shown in Table 3.1 Column (4), those who reported a lockdown of 1-5 weeks, 6-10 weeks, 11-15 weeks increased the time spent online per day more than those reporting no lockdown by 1 hour during lockdown compared to before

Corona, controlling for individual characteristics ($p < 0.01$). People who reported a lockdown length of 16-20 weeks increased time spent online the most compared to those who reported no lockdown, with 1.36 hours difference to the base group of no lockdown ($p < 0.01$).

Lockdown may have a long-term effect on average daily time spent online. As shown in Figure 3.1, although there is a significant decrease in the amount of time that people expect to spend online after Corona compared to during lockdowns, the expected level is still significantly higher than that before Corona (7.36 hours vs 6.72 hours, n=17728, $p < 0.001$, two-sided t-test). On average, as the number of the reported governmental interventions increases by 1, the increase in time spent online increases by 0.038 hour in expectation after Corona compared to before Corona ($p < 0.01$). This implies that stricter lockdown policies had a long-lasting impact on people's expectation about changes in online time. As shown in Table 3.2 Columns (2) and (4), we found a positive and statistically significant effect across all lockdown durations on the expected long-term change of online time. Data show that longer lockdown induces a stronger shift in expecting a longer time spent online after Corona. The change in behavior is not statistically different between those who reported no lockdown and those who did not know the length of lockdown or whether there was a lockdown. This result implies that a longer lockdown might make people integrate their digital lives more deeply, contributing to the formation of new digital habits in the long run. Comparing Table 3.1 and Table 3.2, we observed that the changes of time spent online were more pronounced in the short run, and only partially sustained in expectation after Corona. While the strictness of the lockdown had a strong and significant effect on the increase in the time spent online during the lockdown period, the magnitude of this effect decreases when looking at expectations for post-pandemic behavior (see Table 3.1). This shows that people don't expect to maintain the full extent of online habits formed during lockdowns.

Sociodemographic Variation

Demographic characteristics and other individual-level controls significantly explain variation in the change of online behavior during and after lockdowns. As expected, younger people increased their average daily time spent online more than older people in all model specifications. For instance, people aged 18 to 24 on average spent 2.5 hours more online during lockdown than before Corona, whereas people aged 55 to 65 reported a 1.6 hour increase. Female respondents reported significantly higher increase in online time during lockdowns (Table 3.1 Column (4): $\beta = 0.36, p < 0.01$), although this gender difference diminishes and becomes statistically insignificant in expectation after Corona compared to before Corona. Educational attainment is another strong predictor. Those with a college-level education or higher reported between 0.26 and 0.39 additional hours online, both during and after lockdowns ($p < 0.01$). This could be a result of a higher increase in teleworking time among those with higher educational attainment.

Data shows that employed and self-employed people changed less than the unemployed and the retired individuals both during lockdown and in expectation after Corona. We also control for whether respondents lived with young children at home and we found that household composition matters during lockdowns. We expect those who live with small kids might change their behavior less as they might need to care for the children at home and have less time for themselves. However, we do not observe a significant difference among those who live with kids aged 0 to 6 and who do not. Living with children aged 7 to 18 is positively associated with increased online time during lockdowns (Table 3.1 (4): $\beta = 0.15, p < 0.01$), potentially reflecting the digital demands of homeschooling. Similarly, living with elderly persons (65+) is associated with greater increase in online activity (Table 3.1 (4): $\beta = 0.24, p < 0.01$).

Financial stress during lockdowns is a robust and significant predictor of increased online activity. Individuals experiencing higher stress reported over half an hour more online time per day during lockdown compared to before Corona (Table 3.1 (4): $\beta = 0.58, p < 0.01$), possibly using online tools to manage financial uncertainty or as coping mechanisms. Health status also plays a role during the lockdown: those with better self-perceived health report higher increase in online time, which may reflect greater digital engagement for leisure or remote work among healthier individuals.

These results show that beyond lockdown policy, individual characteristics and personal circumstances including financial stress level, health status, family structure, and employment shaped how individuals adapted their online behaviors during the pandemic and how they expect these habits to evolve afterward.

Table 3.1: Change in time spent online per day during lockdowns vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.16***		0.19***	
	(0.01)		(0.009)	
Lockdown length:				
1-5 weeks		0.61***		0.94***
		(0.16)		(0.14)
6-10 weeks		0.67***		1.01***
		(0.15)		(0.14)
11-15 weeks		0.58***		0.95***
		(0.16)		(0.14)
16-20 weeks		0.89***		1.36***
		(0.17)		(0.16)
More than 20 weeks		0.58***		1.10***
		(0.18)		(0.16)
unknown		−0.027		0.026
		(0.17)		(0.17)
Age			−0.014***	−0.012***
			(0.003)	(0.003)
Female			0.28***	0.36***
			(0.057)	(0.057)
Married			0.020	0.066
			(0.066)	(0.066)
College-level edu or higher			−0.025	−0.0054
			(0.061)	(0.061)
Employed			−0.28***	−0.36***
			(0.066)	(0.066)
Self-employed			−0.41***	−0.48***
			(0.098)	(0.099)
Student			0.051	0.060
			(0.12)	(0.13)
Household size			0.077***	0.11***
			(0.025)	(0.026)
Risk attitude in general			0.0061	0.048
			(0.035)	(0.036)
Risk attitude in health issues			−0.076**	−0.13***
			(0.035)	(0.035)
Financial stress during lockdown			0.53***	0.58***
			(0.029)	(0.029)
Health status			0.11***	0.15***
			(0.030)	(0.030)
Live with kids age 0-6			0.061	0.078
			(0.079)	(0.080)
Live with kids age 7-18			0.18**	0.15**
			(0.069)	(0.070)
Live with elderly above 65			0.23**	0.24***
			(0.089)	(0.090)
Constant	1.49***	1.78***	1.44***	1.38***
	(0.29)	(0.42)	(0.15)	(0.19)
R-squared	0.038	0.01	0.071	0.053
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent online per day during lockdowns compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *p < 0.1; **p < 0.05, ***p < 0.01. Standard errors in parenthesis.

Table 3.2: Expected change in time spent online per day after Corona vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.038***		0.038***	
	(0.007)		(0.006)	
Lockdown length:				
1-5 weeks		0.33***		0.26***
		(0.11)		(0.096)
6-10 weeks		0.37***		0.30***
		(0.10)		(0.093)
11-15 weeks		0.30***		0.24**
		(0.11)		(0.098)
16-20 weeks		0.60***		0.54***
		(0.12)		(0.11)
More than 20 weeks		0.52***		0.45***
		(0.12)		(0.11)
unknown		0.13		0.071
		(0.12)		(0.11)
Age			−0.0069***	−0.0062***
			(0.002)	(0.002)
Female			0.020	0.032
			(0.039)	(0.039)
Married			0.086*	0.093**
			(0.045)	(0.045)
College-level edu or higher			0.068	0.066
			(0.042)	(0.042)
Employed			−0.17***	−0.19***
			(0.045)	(0.046)
Self-employed			0.064	0.037
			(0.068)	(0.068)
Student			0.16*	0.18**
			(0.086)	(0.086)
Household size			−0.0020	0.0025
			(0.018)	(0.017)
Risk attitude in general			−0.13***	−0.12***
			(0.025)	(0.025)
Risk attitude in health issues			0.15***	0.13***
			(0.024)	(0.024)
Financial stress during lockdown			0.15***	0.16***
			(0.020)	(0.020)
Health status			0.025	0.028
			(0.021)	(0.021)
Live with kids age 0-6			0.060	0.064
			(0.055)	(0.055)
Live with kids age 7-18			0.071	0.064
			(0.048)	(0.048)
Live with elderly above 65			0.082	0.078
			(0.062)	(0.062)
Constant	0.48***	0.35***	0.65***	0.53***
	(0.098)	(0.12)	(0.11)	(0.13)
R-squared	0.003	0.003	0.015	0.015
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent online per day in expectation after Corona compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *p < 0.1; **p < 0.05, ***p < 0.01. Standard errors in parenthesis.

3.3.2 Streaming Services

On average, there is a 36.5% increase in the reported time spent on streaming services per day during lockdown compared to before Corona and people expected to spend 5.3% more time on streaming services after Corona compared to before (n=17728, $p < 0.01$, two-sided t-test).

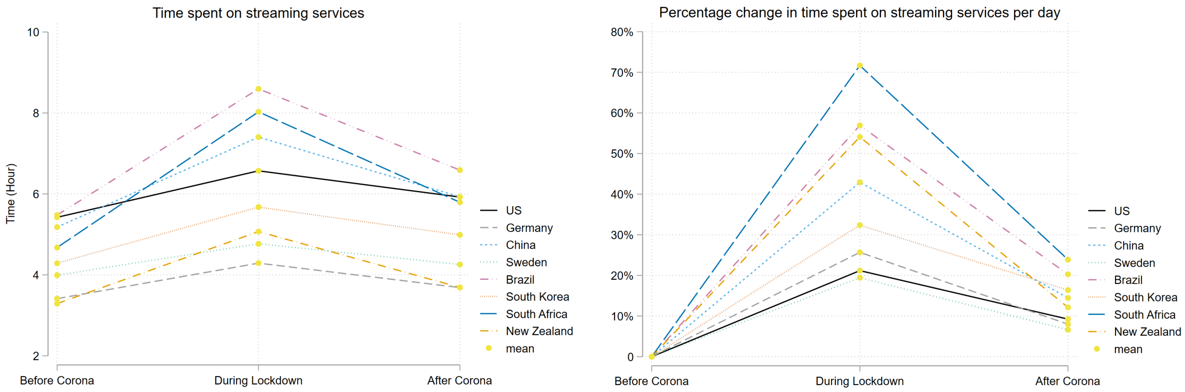


Figure 3.2: The figure exhibits the absolute change (left panel) and the percentage change (right panel) of time spent on streaming services per day by time period and country.

The lockdown highly affects the change in the usage of streaming services (see Figure 3.2) and regression results show that both the strictness of the lockdown and the duration of the lockdown play a significant role in the change of online streaming time. As shown in Table 3.3 Column (1), one more self-reported lockdown intervention leads to a 0.13 hour increase in the change of the average daily time spent on streaming services during lockdown compared to before Corona. People expected to use online streaming services slightly more after Corona than before Corona (see Table 3.4 Column (1), $\beta = 0.028, p < 0.01$). The coefficient is significant but very small. A longer lockdown is positively correlated with higher increase in the time spent on streaming services per day during the lockdown compared to before Corona. As indicated in Table 3.3 Column (4), the coefficients of different lockdown lengths are all significant, with coefficients of lockdown length of 16- 20 weeks being the highest ($\beta = 1.17, p < 0.01$). When we look at the long-term effect of the lockdown duration, coefficients for lockdown length below 16 weeks become statistically insignificant. Those who exposed to 16–20 week lockdowns expected to increase their daily streaming by 0.36–0.41 hours ($p < 0.01$) after Corona. This implies that longer lockdown seems to shape a stronger shift in online streaming habit in the long run.

The regression results also show individual-level heterogeneity in the change of online streaming time. Consistent with demographic variations in the overall time spent online, the change in time spent on streaming services was higher among younger people both during lockdown and in expectation after Corona. Women reported greater increases than men (during vs before: $\beta = 0.41, p < 0.01$, after vs before $\beta = 0.1, p < 0.01$). The retired and the unemployed also increased more time spent on streaming services than domestic workers during lockdown compared to before Corona. A greater financial stress level during lockdown also leads to a higher increase in the time spent on streaming services per day both during lockdown and in expectation after Corona (see Table 3.4 Column 3). Psychological condition also influences streaming habits. Individuals who reported greater financial stress level were significantly more likely to increase time spent on streaming services both during the lockdown and in expectation after Corona. For instance, one standard deviation increase in financial stress level was associated with 0.4 hour more increase in the change of online streaming time during lockdown and 0.14 hour more after Corona compared to before Corona ($p < 0.01$). Individuals living in a larger household also increased time spent on streaming services more than those living in a smaller household during lockown compared to before Corona (see Table 3.3 Column (4) $\beta = 0.11, p < 0.01$).

Table 3.3: Change in time spent on streaming services per day during lockdowns vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.13***		0.16***	
	(0.009)		(0.008)	
Lockdown length:				
1-5 weeks		0.43***		0.74***
		(0.15)		(0.13)
6-10 weeks		0.41***		0.76***
		(0.15)		(0.13)
11-15 weeks		0.31**		0.69***
		(0.15)		(0.13)
16-20 weeks		0.74***		1.17***
		(0.16)		(0.15)
More than 20 weeks		0.54***		1.00***
		(0.17)		(0.15)
unknown		−0.11		−0.032
		(0.16)		(0.16)
Age			−0.020***	−0.018***
			(0.002)	(0.002)
Female			0.41***	0.47***
			(0.054)	(0.054)
Married			−0.018	0.021
			(0.062)	(0.063)
College-level edu or higher			−0.027	−0.0100
			(0.058)	(0.058)
Employed			−0.26***	−0.33***
			(0.062)	(0.063)
Self-employed			−0.21**	−0.28***
			(0.093)	(0.094)
Student			−0.093	−0.079
			(0.12)	(0.12)
Household size			0.083***	0.11***
			(0.024)	(0.024)
Risk attitude in general			0.0097	0.047
			(0.034)	(0.034)
Risk attitude in health issues			−0.058*	−0.11***
			(0.033)	(0.034)
Financial stress during lockdown			0.39***	0.43***
			(0.028)	(0.028)
Health status			0.099***	0.13***
			(0.028)	(0.028)
Live with kids age 0-6			0.041	0.054
			(0.075)	(0.076)
Live with kids age 7-18			0.14**	0.11*
			(0.066)	(0.066)
Live with elderly above 65			0.080	0.085
			(0.085)	(0.085)
Constant	1.16***	1.47***	1.35***	1.33***
	(0.24)	(0.31)	(0.15)	(0.18)
R-squared	0.028	0.009	0.059	0.046
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent on streaming services per day during lockdowns compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *p < 0.1; **p < 0.05, ***p < 0.01. Standard errors in parenthesis.

Table 3.4: Change in time spent on streaming services per day in expectation after Corona vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.028***		0.032***	
	(0.007)		(0.006)	
Lockdown length:				
1-5 weeks		0.11		0.11
		(0.11)		(0.095)
6-10 weeks		0.11		0.12
		(0.10)		(0.092)
11-15 weeks		0.056		0.10
		(0.11)		(0.096)
16-20 weeks		0.37***		0.41***
		(0.12)		(0.11)
More than 20 weeks		0.32***		0.36***
		(0.12)		(0.11)
unknown		−0.23*		−0.23**
		(0.12)		(0.11)
Age			−0.0078***	−0.0071***
			(0.002)	(0.002)
Female			0.10***	0.11***
			(0.039)	(0.039)
Married			0.050	0.054
			(0.045)	(0.045)
College-level edu or higher			0.081**	0.073*
			(0.041)	(0.042)
Employed			−0.13***	−0.14***
			(0.045)	(0.045)
Self-employed			0.20***	0.17**
			(0.067)	(0.067)
Student			0.10	0.12
			(0.085)	(0.085)
Household size			0.036**	0.040**
			(0.017)	(0.017)
Risk attitude in general			−0.089***	−0.079***
			(0.024)	(0.024)
Risk attitude in health issues			0.095***	0.079***
			(0.024)	(0.024)
Financial stress during lockdown			0.14***	0.14***
			(0.020)	(0.020)
Health status			0.049**	0.050**
			(0.020)	(0.020)
Live with kids age 0-6			0.026	0.027
			(0.054)	(0.054)
Live with kids age 7-18			−0.035	−0.044
			(0.047)	(0.047)
Live with elderly above 65			−0.0026	−0.010
			(0.061)	(0.061)
Constant	0.50***	0.54***	0.56***	0.57***
	(0.11)	(0.13)	(0.10)	(0.13)
R-squared	0.003	0.004	0.013	0.015
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent on streaming services per day in expectation after Corona compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *p < 0.1; **p < 0.05, ***p < 0.01. Standard errors in parenthesis.

3.3.3 Teleworking and Online Studying

We observed a strong effect of the reported lockdown length on the time spent on teleworking or online studying. On average, people reported a 1.29 hours increase in the time spent on teleworking and online studying during Corona lockdown compared to before Corona. Participants expected that there will be a 0.59 hour increase in the time spent on teleworking and online studying after Corona than before Corona ($p < 0.01$, two-sided t-test).

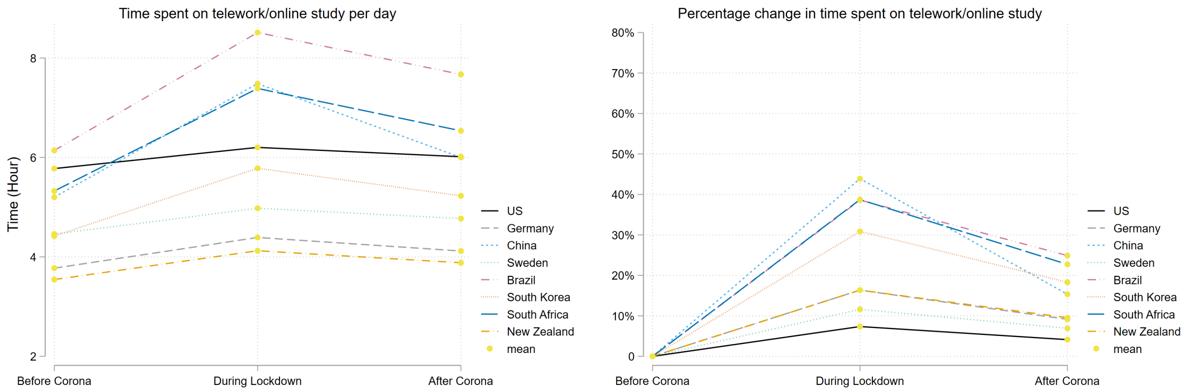


Figure 3.3: The figure exhibits the absolute change (left panel) and the percentage change (right panel) of time spent on teleworking or online studying per day by time period and country.

The regression results show that lockdowns significantly changed individuals' teleworking and online studying behaviors. The strictness of the lockdown, measured by the number of bans, is positively associated with increased time spent on teleworking or online studying. As shown in Table 3.5 Columns (1) and (3), an additional governmental ban leads to an increase of approximately 0.08 to 0.11 hours in the change in time spent on teleworking and online studying per day during lockdown compared to before Corona ($p < 0.01$). Table 3.6 shows that the coefficients for the lockdown strictness is also highly significant for the before - after comparison in terms of the increase in the time spent on teleworking and online studying, but the magnitude is relatively small ($\beta = 0.035, p < 0.01$). This result shows that people shift work and education more to digital formats in the presence of stricter lockdown and there is a long-term effect.

In terms of lockdown length, all durations show statistically significant increases in the change of time spent on teleworking and online studying during lockdown compared to before Corona, with longer lockdowns having a stronger effect (see Column (4) of Table 3.5 and Table 3.6. Specifically, the increase in the change in the time spent on teleworking and online studying during lockdown was the highest for participants who reported having 16-20 weeks ($\beta = 1.11, p < 0.01$). The results imply that not only the strictness but also the duration of lockdowns contributed to a shift toward remote working and online education.

A number of demographic and attitudinal characteristics also significantly influenced changes in teleworking and online studying. Younger individuals tended to increase their time more, with age having a negative effect (-0.021 to -0.019 hours/day per year), which aligns with the higher prevalence of students and early-career professionals in remote education and work.

Females, married individuals, and those with college-level education or higher are all more likely to have increased their time spent teleworking or studying online. For instance, having a college-level education is associated with about 0.31 to 0.39 more hours per day ($p < 0.01$). These findings may reflect both greater access to telework-compatible jobs and higher enrollment in online education programs among these groups.

Students show the largest increase, with over 1.08 hours/day more time spent during lockdowns, which is consistent with the broad closure of in-person classes and the pivot to digital learning environments. Conversely, self-employed individuals spent significantly less time on teleworking or studying online (around -0.21 hours/day), likely reflecting a mismatch between self-employment tasks and digital platforms.

Larger household sizes are associated with higher increases in time spent teleworking or studying, possibly reflecting collective engagement in online work or study environments, or constrained ability to leave the household. Moreover, individuals who reported higher financial stress during lockdowns and those with better perceived health also report more increase in the time spent on teleworking or online studying.

Finally, the presence of school-aged children (7–18) in the household is positively associated with increased teleworking or online studying time, perhaps reflecting parental support in children's online education or simultaneous remote work setups.

Table 3.5: Change in time spent on teleworking or online studying per day during lockdowns vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.084***		0.11***	
	(0.010)		(0.009)	
Lockdown length:				
1-5 weeks		0.58***		0.51***
		(0.16)		(0.15)
6-10 weeks		0.53***		0.57***
		(0.16)		(0.14)
11-15 weeks		0.45***		0.58***
		(0.17)		(0.15)
16-20 weeks		0.87***		1.11***
		(0.18)		(0.17)
More than 20 weeks		0.43**		0.81***
		(0.19)		(0.17)
unknown		0.22		0.20
		(0.18)		(0.18)
Age			−0.021***	−0.019***
			(0.003)	(0.003)
Female			0.17***	0.21***
			(0.060)	(0.060)
Married			0.28***	0.31***
			(0.070)	(0.070)
College-level edu or higher			0.38***	0.39***
			(0.064)	(0.065)
Employed			0.099	0.058
			(0.070)	(0.070)
Self-employed			−0.15	−0.21**
			(0.10)	(0.10)
Student			1.06***	1.08***
			(0.13)	(0.13)
Household size			0.063**	0.080***
			(0.027)	(0.027)
Risk attitude in general			−0.074*	−0.044
			(0.038)	(0.038)
Risk attitude in health issues			0.055	0.015
			(0.037)	(0.037)
Financial stress during lockdown			0.27***	0.30***
			(0.031)	(0.031)
Health status			0.14***	0.16***
			(0.032)	(0.032)
Live with kids age 0-6			0.094	0.11
			(0.084)	(0.085)
Live with kids age 7-18			0.23***	0.21***
			(0.073)	(0.074)
Live with elderly above 65			0.020	0.020
			(0.095)	(0.095)
Constant	0.84***	0.80***	0.53***	0.44**
	(0.27)	(0.30)	(0.16)	(0.20)
R-squared	0.013	0.005	0.04	0.035
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent on teleworking or online studying per day during lockdowns compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *p < 0.1; **p < 0.05, ***p < 0.01. Standard errors in parenthesis.

Table 3.6: Change in time spent on teleworking or online studying per day in expectation after lockdowns vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.023***		0.035***	
	(0.007)		(0.006)	
Lockdown length:				
1-5 weeks		0.26**		0.20*
		(0.12)		(0.11)
6-10 weeks		0.19*		0.15
		(0.12)		(0.10)
11-15 weeks		0.22*		0.22**
		(0.12)		(0.11)
16-20 weeks		0.45***		0.47***
		(0.13)		(0.12)
more than 20 weeks		0.22		0.27**
		(0.14)		(0.12)
unknown		−0.031		−0.090
		(0.13)		(0.13)
Age			−0.011***	−0.011***
			(0.002)	(0.002)
Female			0.089**	0.10**
			(0.044)	(0.044)
Married			0.076	0.081
			(0.051)	(0.051)
College-level edu or higher			0.088*	0.085*
			(0.047)	(0.047)
Employed			0.0034	−0.014
			(0.051)	(0.051)
Self-employed			0.18**	0.16**
			(0.076)	(0.076)
Student			0.66***	0.67***
			(0.095)	(0.096)
Household size			0.0083	0.014
			(0.020)	(0.019)
Risk attitude in general			−0.10***	−0.095***
			(0.027)	(0.027)
Risk attitude in health issues			0.043	0.029
			(0.027)	(0.027)
Financial stress during lockdown			0.16***	0.17***
			(0.023)	(0.022)
Health status			0.093***	0.095***
			(0.023)	(0.023)
Live with kids age 0-6			0.031	0.031
			(0.061)	(0.061)
Live with kids age 7-18			0.14**	0.13**
			(0.053)	(0.053)
Live with elderly above 65			0.084	0.084
			(0.069)	(0.069)
Constant	0.58***	0.49**	0.53***	0.50***
	(0.16)	(0.23)	(0.12)	(0.15)
R-squared	0.003	0.003	0.018	0.018
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent on teleworking or online studying per day in expectation after lockdowns compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *p < 0.1; **p < 0.05, ***p < 0.01. Standard errors in parenthesis.

3.3.4 Online Video Call Platforms

Short-run analysis

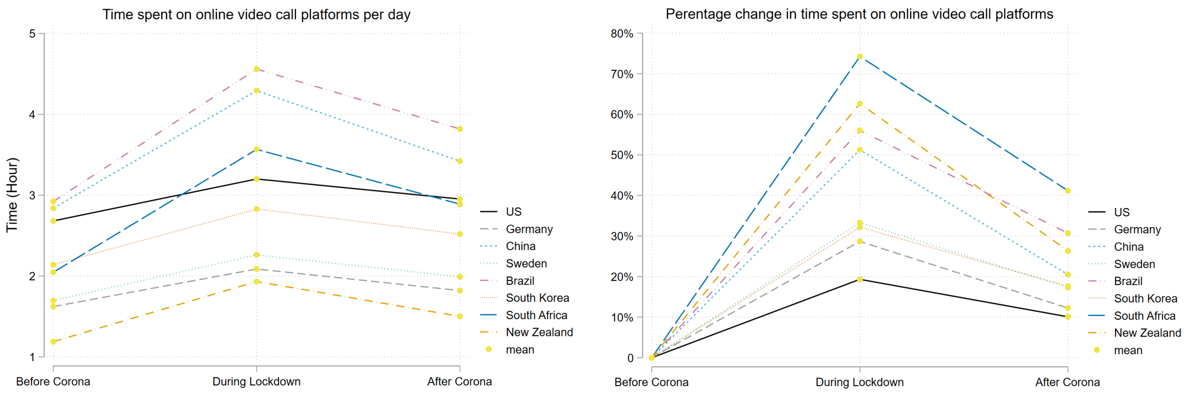


Figure 3.4: The figure exhibits the absolute change (left panel) and the percentage change (right panel) of time spent on online video call platforms such as Zoom per day by time period and country.

Online video call platforms such as Zoom become very popular since the Corona pandemic outbreak as many companies and businesses were forced to shift their work online during the lockdown. The regression results show that people who experienced stricter lockdown increased the usage of online video call platforms more than those who reported experiencing no lockdown. As shown in Table 3.7, the number of governmental bans is positively and significantly associated with more increase in the time spent on these platforms (coefficient around 0.073–0.084 across specifications). Similarly, the length of lockdowns had a positive impact: longer lockdown durations are associated with larger increases in usage time up to 16-20 weeks. Notably, individuals who reported 16–20 weeks of lockdown experienced the largest increase on the time spent on online video call platforms ($\beta = 0.55, p < 0.01$, see Column (4) of Table 3.7). This result further shows that prolonged lockdown measures contributed to a stronger shift towards more teleworking and online education.

Individual characteristics also played an important role. Students reported a significantly higher increase in the time spent on online video call platforms such as Zoom than non-students during the lockdown compared to before Corona ($\beta = 0.58, p < 0.01$). Females, married individuals, and those with higher education levels also exhibited greater increases in time spent on online video call platforms. This could be due to a higher demand for work- and family-related video communication. Furthermore, financial stress during lockdowns is positively associated with greater increase in the use of video platforms ($\beta = 0.19, p < 0.01$, see Table 3.7). Those under financial stress may have relied more on online communication to maintain social ties and seek support networks remotely.

Long-run analysis

The expected use of online video call platforms remained above pre-pandemic levels (after vs. before: 2.8 vs. 2.36, $p < 0.01$, two-sided t-test), though the magnitude of increase was smaller than during lockdowns (during vs. before: 3.29 vs. 2.36, $p < 0.01$, two-sided t-test). As shown in Table 3.8, the number of bans still positively predicts higher increase in the expected future usage, but with reduced coefficients (0.027–0.032 compared to 0.073–0.084 during lockdowns). Longer lockdown durations also have a positive effect, but again, the effect sizes are smaller compared to that during lockdown. This result suggests that habits formed during the pandemic, such as remote work meetings, virtual family gatherings, and online education, may have partially transitioned into a new norm. Notably, students again show the largest expected increase in the change of the usage of online video call platforms in the post-Corona period ($\beta = 0.46, p < 0.01$, see Table 3.8), but the increase is slightly less than during lockdowns compared to before Corona.

Overall, the results suggest that Corona lockdown potentially leads to a behavioral shift in the way people work and study. Lockdown measures, particularly their duration, were crucial drivers of the increase in online video call platforms, teleworking and online studying. Although some rebound is expected in the post-pandemic time, the persistence of increased usage levels suggests lasting changes in communication patterns. This supports the view that the pandemic accelerated the digitalization of daily life, not just temporarily but with long-term consequences for work, education, and social interactions. These findings imply that service providers such as Zoom and Microsoft Team may continue to see increased demand even in a post-pandemic world, especially from sectors like education and remote work environments where hybrid models have become more mainstream.

Table 3.7: Change in time spent on online video call platforms per day during lockdowns vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.073***		0.084***	
	(0.006)		(0.005)	
Lockdown length:				
1-5 weeks		0.21**		0.23***
		(0.096)		(0.086)
6-10 weeks		0.20**		0.27***
		(0.095)		(0.084)
11-15 weeks		0.26***		0.38***
		(0.098)		(0.087)
16-20 weeks		0.39***		0.55***
		(0.11)		(0.097)
More than 20 weeks		0.16		0.39***
		(0.11)		(0.099)
unknown		0.040		0.094
		(0.11)		(0.10)
Age			−0.014***	−0.013***
			(0.002)	(0.002)
Female			0.19***	0.22***
			(0.035)	(0.035)
Married			0.14***	0.17***
			(0.040)	(0.041)
College-level edu or higher			0.28***	0.30***
			(0.037)	(0.038)
Employed			0.16***	0.14***
			(0.040)	(0.041)
Self-employed			−0.25***	−0.29***
			(0.060)	(0.061)
Student			0.58***	0.58***
			(0.076)	(0.077)
Household size			0.016	0.031**
			(0.016)	(0.016)
Risk attitude in general			−0.025	−0.0025
			(0.022)	(0.022)
Risk attitude in health issues			0.012	−0.015
			(0.022)	(0.022)
Financial stress during lockdown			0.16***	0.19***
			(0.018)	(0.018)
Health status			0.089***	0.11***
			(0.018)	(0.018)
Live with kids age 0-6			0.061	0.070
			(0.049)	(0.049)
Live with kids age 7-18			0.18***	0.17***
			(0.043)	(0.043)
Live with elderly above 65			0.087	0.091*
			(0.055)	(0.055)
Constant	0.57***	0.75***	0.40***	0.47***
	(0.14)	(0.15)	(0.094)	(0.12)
R-squared	0.021	0.005	0.052	0.041
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent on online video call platforms per day during lockdowns compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *p < 0.1; **p < 0.05, ***p < 0.01. Standard errors in parenthesis.

Table 3.8: Change in time spent on online video call platforms per day in expectation after Corona vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.027***		0.032***	
	(0.004)		(0.004)	
Lockdown length:				
1-5 weeks		0.20***		0.17***
		(0.069)		(0.061)
6-10 weeks		0.12*		0.11*
		(0.067)		(0.060)
11-15 weeks		0.16**		0.18***
		(0.070)		(0.062)
16-20 weeks		0.31***		0.34***
		(0.076)		(0.069)
More than 20 weeks		0.080		0.14**
		(0.077)		(0.070)
unknown		0.053		0.063
		(0.076)		(0.073)
Age			−0.0054***	−0.0051***
			(0.001)	(0.001)
Female			0.057**	0.069***
			(0.025)	(0.025)
Married			0.058**	0.067**
			(0.029)	(0.029)
College-level edu or higher			0.15***	0.16***
			(0.027)	(0.027)
Employed			0.13***	0.12***
			(0.029)	(0.029)
Self-employed			−0.000,51	−0.015
			(0.043)	(0.043)
Student			0.46***	0.46***
			(0.055)	(0.055)
Household size			0.021*	0.026**
			(0.011)	(0.011)
Risk attitude in general			−0.023	−0.015
			(0.016)	(0.016)
Risk attitude in health issues			0.018	0.0078
			(0.015)	(0.015)
Financial stress during lockdown			0.080***	0.087***
			(0.013)	(0.013)
Health status			0.038***	0.044***
			(0.013)	(0.013)
Live with kids age 0-6			0.0081	0.011
			(0.035)	(0.035)
Live with kids age 7-18			0.018	0.013
			(0.030)	(0.031)
Live with elderly above 65			−0.022	−0.017
			(0.039)	(0.039)
Constant	0.33***	0.33***	0.13*	0.12
	(0.085)	(0.11)	(0.068)	(0.084)
R-squared	0.006	0.003	0.022	0.02
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent on online video call platforms per day in expectation after Corona compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *p < 0.1; **p < 0.05, ***p < 0.01. Standard errors in parenthesis.

3.3.5 Digital Gaming

Our data show that the time spent on digital gaming increased significantly during the COVID-19 lockdowns compared to before Corona (5.74 vs 4.38, $p < 0.01$, two-sided t-test). As shown in Figure 3.5, there is a substantial cross-country variation, with the highest percentage increase observed in South Africa and Brazil. In addition, people expected to spend less time on digital gaming in the post-Corona time, but still slightly more than the pre-Corona period (4.81 vs 4.38, $p < 0.01$, two-sided t-test).

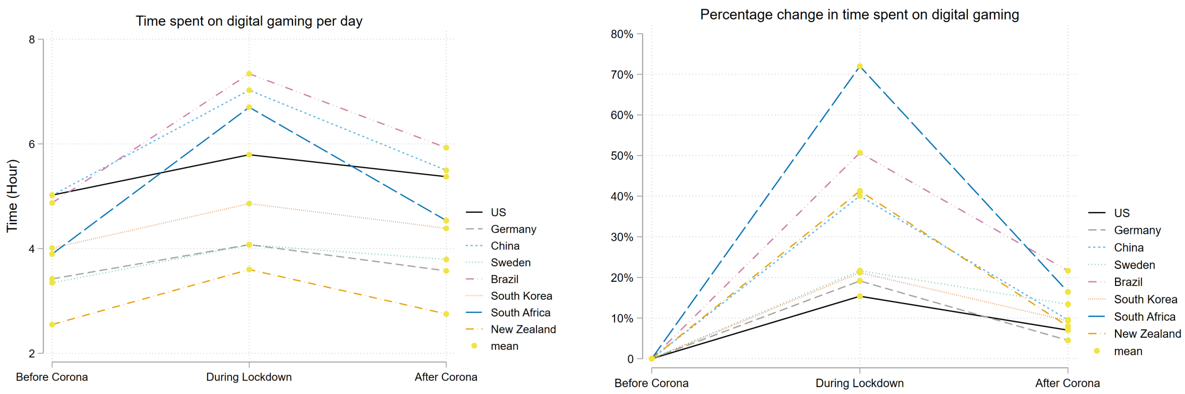


Figure 3.5: The figure exhibits the absolute change (left panel) and the percentage change (right panel) of time spent on digital gaming per day by time period and country.

The regression results show a strong effect of lockdown on digital gaming behavior. The number of bans, used as a proxy for lockdown strictness, is associated with a greater increase in the amount of time that people spent on digital gaming during the pandemic. Each additional governmental restriction is associated with an increase of 0.13 hour in the change in time spent on digital gaming per day during lockdowns ($p < 0.01$). The duration of lockdowns also contributed to a larger increase in the time spent on digital gaming. Longer lockdowns up to 20 weeks led to more increase in the change of digital gaming time. As shown in Table 3.9 Column (4), lockdowns lasting 16–20 weeks resulted in a 0.97-hour increase in the change of daily digital gaming time ($p < 0.01$), while those longer than 20 weeks contributed to 0.66 hour per day more increase in the change of gaming time (both $p < 0.01$).

Interestingly, as shown in Table 3.10, while the magnitude of the change decreased, people who reported stricter lockdown experience expected to increase more time spent on digital gaming after the pandemic compared to before Corona ($\beta = 0.028, p < 0.01$). Although the coefficients of most shorter lockdown durations no longer show significant effects in the long-run analysis, those who experienced 16–20 week lockdowns expected to spend 0.2 hours more per day on gaming, and those in more than 20-week lockdowns expected 0.22 hours per day more (Table 3.10 Column (4), $p < 0.1$).

Individual Heterogeneity

Results show a significant individual variation in the changes in digital gaming behavior. The increase in online gaming time decreases with age, with each additional year associated with 0.025–0.026 fewer hour per day of increased gaming during lockdowns, and 0.008 fewer hour per day in post-pandemic expectations. This suggests that the increase in online gaming were driven primarily by young people, consistent with global trends in gaming demographics. Women tended to report lower increases in gaming both during and after lockdowns, however, the gender coefficients are not statistically significant.

Employment status also has a significant effect on the change in time spent on online gaming. The increase in the change in online gaming time is lower among employed individuals than the unemployed during lockdowns compared to before Corona ($\beta = 0.41, p < 0.01$). This pattern is consistent in post-pandemic expectations, indicating a persistent gap in gaming behavior across employment groups. In contrast, self-employed individuals show higher increases in gaming behavior in the post-pandemic time compared to before Corona ($\beta = 0.2, p < 0.01$, see Column (2) of Table 3.10). Notably, students also reported a lower increase in online gaming time than non-students.

In addition, those experiencing financial stress reported greater increase in online gaming time. Financial stress during lockdowns is associated with an increase of 0.38 hours/day more time spent on online gaming during lockdowns and 0.08 hours/day more additional time in expectation after Corona. These results suggest that gaming may have served both as a coping mechanism and an affordable entertainment alternative for people under financial pressure.

As shown in Table 3.9, household characteristics also influences the change in online gaming behavior. Individuals living with school-aged children (7–18 years) increased gaming time significantly more than those without children during lockdowns. This may reflect both the rising popularity of gaming among adolescents and the role of gaming as a shared recreational activity that helps families cope with lockdown-related stress.

Table 3.9: Change in time spent on digital gaming per day during lockdowns vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.10***		0.13***	
	(0.009)		(0.008)	
Lockdown length:				
1-5 weeks		0.36**		0.46***
		(0.15)		(0.13)
6-10 weeks		0.42***		0.59***
		(0.15)		(0.13)
11-15 weeks		0.35**		0.57***
		(0.15)		(0.13)
16-20 weeks		0.70***		0.97***
		(0.16)		(0.15)
More than 20 weeks		0.61***		0.90***
		(0.17)		(0.15)
unknown		−0.019		−0.037
		(0.16)		(0.16)
Age			−0.026***	−0.025***
			(0.002)	(0.002)
Female			−0.017	0.031
			(0.054)	(0.054)
Married			0.090	0.12**
			(0.063)	(0.063)
College-level edu or higher			−0.046	−0.039
			(0.058)	(0.058)
Employed			−0.41***	−0.46***
			(0.063)	(0.063)
Self-employed			−0.081	−0.14
			(0.094)	(0.094)
Student			−0.44***	−0.41***
			(0.12)	(0.12)
Household size			0.11***	0.13***
			(0.024)	(0.024)
Risk attitude in general			−0.028	0.0052
			(0.034)	(0.034)
Risk attitude in health issues			0.033	−0.011
			(0.033)	(0.034)
Financial stress during lockdown			0.35***	0.38***
			(0.028)	(0.028)
Health status			0.092***	0.11***
			(0.028)	(0.028)
Live with kids age 0-6			−0.031	−0.019
			(0.076)	(0.076)
Live with kids age 7-18			0.22***	0.20***
			(0.066)	(0.066)
Live with elderly above 65			0.099	0.095
			(0.085)	(0.085)
Constant	0.90***	1.06***	1.55***	1.55***
	(0.23)	(0.33)	(0.15)	(0.18)
R-squared	0.019	0.008	0.051	0.043
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent on digital gaming per day during lockdowns compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *p < 0.1; **p < 0.05, ***p < 0.01. Standard errors in parenthesis.

Table 3.10: Change in time spent on digital gaming per day in expectation after Corona vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.028***		0.028***	
	(0.007)		(0.006)	
Lockdown length:				
1-5 weeks		0.066		−0.040
		(0.11)		(0.097)
6-10 weeks		0.11		0.018
		(0.11)		(0.095)
11-15 weeks		−0.0066		−0.064
		(0.11)		(0.099)
16-20 weeks		0.27**		0.20*
		(0.12)		(0.11)
More than 20 weeks		0.30**		0.22*
		(0.12)		(0.11)
unknown		−0.068		−0.13
		(0.12)		(0.12)
Age			−0.0086***	−0.0080***
			(0.002)	(0.002)
Female			−0.032	−0.023
			(0.040)	(0.040)
Married			0.035	0.045
			(0.046)	(0.046)
College-level edu or higher			−0.030	−0.029
			(0.043)	(0.043)
Employed			−0.12***	−0.14***
			(0.046)	(0.046)
Self-employed			0.20***	0.17**
			(0.069)	(0.069)
Student			−0.15*	−0.14*
			(0.087)	(0.087)
Household size			0.0095	0.014
			(0.018)	(0.018)
Risk attitude in general			−0.083***	−0.073***
			(0.025)	(0.025)
Risk attitude in health issues			0.12***	0.10***
			(0.025)	(0.025)
Financial stress during lockdown			0.081***	0.086***
			(0.020)	(0.020)
Health status			−0.0058	0.000,24
			(0.021)	(0.021)
Live with kids age 0-6			−0.12**	−0.11**
			(0.056)	(0.056)
Live with kids age 7-18			0.074	0.070
			(0.048)	(0.049)
Live with elderly above 65			0.0047	−0.0026
			(0.062)	(0.063)
Constant	0.32***	0.38***	0.66***	0.77***
	(0.11)	(0.12)	(0.11)	(0.13)
R-squared	0.001	0.002	0.007	0.008
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent on digital gaming per day in expectation after Corona compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *$p < 0.1$; **$p < 0.05$, ***$p < 0.01$. Standard errors in parenthesis.

3.4 Conclusion

The COVID-19 pandemic imposed sudden and severe constraints on daily life, forcing individuals to rapidly adapt their routines. One of the most striking changes during this period was the accelerated shift toward digital behavior. This chapter investigated how lockdown measures influenced the change of digital habits during the Corona lockdowns and people's long-term expectation on whether these changes will persist when Corona is not a pressing issue anymore.

Drawing on data from eight countries, this study examined changes in a range of digital behaviors, namely, time spent online in general, streaming services, teleworking and online studying, video calls, and online gaming—before, during, and in expectation after the lockdowns. Regression results indicate that both the strictness and duration of lockdowns are significantly associated with greater change in online behavior. However, the effect of lockdown length is nonlinear. Specifically, very long (i.e. more than 20 weeks) lockdowns showed diminishing effects. These findings suggest that behavioral changes to digital environments is not only a function of lockdown duration, but also depends on psychological well-being and social needs. Excessively prolonged lockdowns may lead to fatigue or resistance.

In addition, we examine whether people expect these changes to persist when Corona is not a pressing issue anymore. Respondents generally anticipated that their digital habits would remain elevated even after the pandemic, particularly in areas like teleworking and video communication. Regression results also indicate that there is Sociodemographic variation in the changes of digital habits. Specifically, age, employment status, education, household size, and risk attitudes significantly influence both the extent of digital behavior change and expectations for the persistence of the changes.

4 Advisor Selection and its Impact on Financial Decision-Making

This chapter departs from the pandemic context to explore a broader trend that it accelerated: the growing reliance on digital channels for financial advice. As in-person financial counseling declined during the pandemic, individuals increasingly turn to virtual sources for investment advice. This shift raises questions about the quality and consequences of online peer advice. To investigate this, the current study uses an online experiment to assess the impact of online advice, sourced from Reddit, on an investment task.

4.1 Introduction

According to a recent survey commissioned by Forbes (Egan, 2023), nearly 80% of Gen Zers use social media as a source of financial advise. Indeed, trading platforms, like eToro, encourage this trend by including social media features, e.g., public forums, to their design. Searching for financial advice among peers, such as friends and family, is not a new phenomenon, and has received significant attention from economists (Benartzi and Thaler, 1999; Beshears et al., 2015; Van Rooij et al., 2011; Ambuehl et al., 2022, 2025). However, a rise in the popularity of social media fundamentally changes the nature of seeking peer-advice by introducing an element of choice. While in the past an individual could have consulted at most a few family members and friends, a member of a group on Reddit or a follower of a YouTube channel, has access to hundreds of potential advisors. On the one hand, the abundance of advice may allow one to screen out unqualified advisors, or focus only on those with similar risk preferences. On the other hand, individuals seeking for advice may be tempted to follow advisors with exceptionally

[0] This chapter is joint work with Danisz Okulicz.

high past returns, and consequently end up approaching advisors with a tendency to suggest investments with high exposure to risk.

Some field studies confirm that social media features on trading platforms affect investor behavior (Dorfleitner and Scheckenbach, 2022; Heimer, 2016; Pelster and Hofmann, 2018; Deng et al., 2024; Ammann and Schaub, 2021; Heimer and Simon, 2015). However, an overall assessment of the welfare effects of exposure to online advice is difficult to achieve in field studies. First, a large portion of financial advice is not given in real time by active traders on investment platforms, but rather shared through groups on other social media. Second, welfare consequences of exposure to online advice are difficult to interpret. For example, an increase in risk exposure can be, on the one hand, driven by following misguided advice; on the other hand, it may be an effect of improved understanding of the chosen portfolio and decreased cognitive uncertainty (Enke and Graeber, 2023).

To address these issues, we conduct an experiment in which a group of subjects is asked to build a portfolio consisting of a mix of three artificial assets. One of these assets is first-order stochastically dominated by a combination of the other two. Specifically, two of the assets are risky and perfectly positively correlated—they yield profits in the same state of the world, though they differ in the magnitude of potential gains and losses. The third asset is risk-free. The task is structured so that the less risky of the two correlated assets is dominated by a mix of the riskier and the safe asset. Hence, the optimal choice depends on both a correct understanding of the dominance relationship (i.e., avoiding the dominated asset) and individual risk preferences (which determine the allocation between the safe and risky assets). Subjects in the control group make decisions independently, and subjects in the treatment group first consult with a chosen advisor recruited from a financial advice group on Reddit, the most trusted and the most popular social media for seeking financial advice according to a survey from Forbes (Egan, 2023).

We find evidence supporting both hypothesized effects of exposure to choice of advisors. Subjects in the control group have a strong tendency to follow “naive diversification strategy”, common in real-life pension saving plans (Benartzi and Thaler, 2001). Under naive diversification, economic agents split their endowments between highly correlated assets (e.g., units of different pension funds), mistakenly believing this reduces portfolio risk. In our setup, it implies splitting the investment between the two correlated risky assets, rather than between the undominated risky asset and the safe asset. By contrast, subjects in the treatment group are less prone to naive diversification: they invest less in the dominated asset and more frequently select fully undominated portfolios. However, these portfolios tend to be riskier in terms of worst-case outcomes. Importantly, treated subjects do not follow advice blindly. Instead, they consider their own risk preferences and tend to select advisors with similar risk attitudes. Nearly half of the treated participants modify the suggested portfolios to reduce perceived risk. Unfortunately, these adjustments often fail to meaningfully decrease risk while lowering potential earnings as some elements of naive diversification persist, even among advised subjects. Nonetheless, even subjects who make suboptimal adjustments to the advised portfolios outperform those in the control group.

To evaluate the overall effect of exposure to the choice of advice, we ask subjects to provide us with certainty equivalent of their chosen portfolio. Subjects exposed to advice report higher valuations of the chosen portfolio. While the effect is not statistically significant for the entire sample, it is significant for the subjects whose choices are consistent with expected utility theory. The notion that access to advisor choice enhances welfare is further supported by observed changes in portfolio composition across treatments. Specifically, a greater proportion of treated subjects allocate at least part of their endowment to the safe asset compared to the control group. Any increase in risk exposure primarily results from reallocating funds from the dominated to the undominated risky asset. Moreover, our simulations suggest that a substantial share of untreated subjects would benefit from receiving advice, whereas only a small fraction of treated subjects are adversely affected by it.

4.2 Literature Review

Our paper relates to several strands of literature. First, it contributes to the literature investigating advice-seeking behavior in finance. A series of recent studies has indicated that advice-seeking behavior in finance is influenced by various factors such as demographic factors, financial literacy, and behavioral biases (Çelen et al., 2010; Hung and Yoong, 2013; Kramer, 2016; Agnew et al., 2018; Hsu, 2022). For instance, studies show that people with lower financial literacy are less likely to seek professional advice (Calcagno and Monticone, 2015) and behavioral biases such as overconfidence has a negative impact on advice-seeking behavior (Hsu, 2022). Advice seeking, receiving and choosing have also been studied beyond the framework of financial decision-making (see Kämmer et al. 2023 for a comprehensive literature review). Our paper contributes to this strand of literature by investigating how people choose financial advisors given certain attributes of the financial advisor.

There is also a large body of literature that examines the impact of professional financial advice on investors, and the results are mixed. Some studies find positive effects, such as improved portfolio diversification (Bluethgen et al., 2008; Kramer, 2012), while others suggest that financial advice has a limited impact on household financial decisions (Stolper, 2018) and advisors could even hurt trading performance (Hoechle et al., 2017), reinforce traders' biases (Mullainathan et al., 2012), suffer from biases themselves (Linnainmaa et al., 2021), or do not use their skills when making decisions on behalf of their clients (Stefan et al., 2022). In contrast, our study shifts the focus towards advice received from non-professionals. We demonstrate that online peer advice can improve portfolio choices.

The study by Ambuehl et al. (2025) holds specially significant relevance for our research framework. Based on the experimental design established by Ambuehl et al. (2022), the authors empirically demonstrate that face-to-face communication with a randomly assigned peer enhances subjects' consistency in choosing between immediate and delayed payments, when the delayed alternative is presented using different frames.

Similar to their design, our design allows for following even well-meaning advice to have a detrimental effect on subjects' welfare, as the optimal decision is not only complex, but also depends on subjects' preferences which potentially diverge from those of the advisor. However, our design diverges in some key respects. First, we focus on decision-making under uncertainty rather than time preference. Second, we present subjects with a treatment closer to online advice seeking, in that the subjects can choose one advisor from a list but do not interact with them face-to-face. Finally, we allow our subjects to choose their own advisors. While these differences could potentially harm the quality of advice, we still find evidence of its overall positive effect. To our knowledge, the only experimental study that directly investigates online financial advice is Agnew et al. (2018). In contrast to our focus on the welfare implications of advisor selection, their work examines how advice-seekers form impressions of advisors and how these perceptions can be influenced.

Our research contributes to the extensive experimental literature exploring the influence of peer effects on decisions under uncertainty. Noteworthy studies in this domain include those by Bougheas et al. (2013); Bursztyn et al. (2014); Lahno and Serra-Garcia (2015); Gioia (2017); Lopera and Marchand (2018); Gortner and van der Weele (2019); Schwerter (2024); Baillon et al. (2016) and Keck et al. (2014). Gortner and van der Weele (2019) show that the impact of peer effects can be increased by highlighting high-earning traders, and Gioia (2017) demonstrate that peer effects are stronger under shared group identity. Using a lab-in-the-field experiment, Lopera and Marchand (2018) find that social conformity affects risk aversion, as individuals tend to align their risk preferences with their peers. In contrast to these studies, which typically focus on the exchange of information and preferences among peers, our study examine the effect of explicit advice provided by strangers. Additionally, we introduce a novel element by allowing participants to select their advisor from a pool, mimicking real-world advice-seeking behavior in online environments. Finally, we directly measure welfare of participants, and we are able to demonstrate that advice has at least some positive effect on the welfare.

Few studies explicitly link peer effect with advice giving in an experimental setup. Bougheas et al. (2013) study a setup in which groups have to take a decision under uncertainty. They show that while group decisions tend to be riskier than individual decisions, consultation with peers does not affect the riskiness of the choice. In contrast, our research suggests that when individuals have the opportunity to select an advisor, the riskiness of the chosen investment portfolio tends to increase. Keck et al. (2014) propose a similar design but focus on the role of ambiguity, and show that communication within the group results in individuals making more ambiguity-neutral decisions. Baillon et al. (2016) adjust the design to focus on rationality of choices, and show that communication within group is sufficient to reduce the likelihood of making stochastically dominated choices.

Our study also contributes to an emerging field of social finance. Social finance is characterized by peer effects in financial decision-making and the influence of social connections on investment behaviors (see Kuchler and Stroebel 2021 for a literature review). Hvide and Östberg (2015) found that social interactions with colleagues at work significantly influence individual investors' trading activity and stock selection, but do not improve investment quality. Bursztyn et al. (2014) investigated the mechanisms underlying peer effects on investment decision in a field experiment with financial brokerage and they found that both peers' preferences for assets and peers' possession of assets have an impact on one's own investment decision. Schwerter (2024) finds that observing higher earnings of peers leads to less risk-averse financial decisions, consistent with prospect theory's social reference points. Balakina et al. (2024) explicitly study the role of financial advice from peers, especially family and friends, and report that personal financial advice leads to more diversified investment choices. In contrast to previous studies, our research uniquely examines how the choice of advisors from a finance self-help social media platform influences investment decisions, taking into account both its effects on risk taking and overall quality of the investment.

Copy-trading, that is an option of copying portfolios of other investor directly, is a related feature of social finance. The crucial difference between copy trading and the advice seeking behavior is that, first, the investors can adjust the portfolios suggested by the advisors to better fit their preferences, and, second, have access to explanations for why a given advisor suggests investing in a particular portfolio. Both features have a potential of mitigating negative effects of copy trading. The effects of copy trading were experimentally explored by Apesteguia et al. (2020), who show that the ability to copy investments of others significantly increases riskiness of chosen portfolios, especially among subjects with low-risk tolerance. Our findings similarly indicate that selecting an advisor tends to increase portfolio riskiness. However, as anticipated, the influence of advice on risk-taking is moderate, resulting in overall improved welfare outcomes for individuals receiving advice.

Several recent studies have examined the role of social interactions on online trading platforms. Dorfleitner and Scheckenbach (2022), Heimer (2016) and Pelster and Hofmann (2018) focus on the reputational concerns of traders on social trading platforms and demonstrate that these may result in overconfidence and disposition effects. Deng et al. (2024), Heimer and Simon (2015) and Ammann and Schaub (2021) examine the relationship between advisors and advisees more directly. These studies demonstrate potential shortcomings of social trading. In particular, return-chasing may convince individual investors to engage in active trading and diminish their returns. Rather than focusing on dynamic trading strategies, we focus on the trade-off between risk and return – a setup better suited to sharing financial advice on platforms not specifically designed for trading, such as Facebook, YouTube, or Reddit.

4.3 Experimental Design

This section outlines the study design, the method used to elicit advice, the experimental procedure, and the hypotheses under investigation.

4.3.1 Experimental Task

Our experiment consists of three parts. Part 1 contains the main financial decision-making task. Part 2 elicits the certainty equivalent of the investment portfolio in Part 1. Part 3 contains a questionnaire. We conducted the experiment in a control group and a treatment group, which differed in whether subjects can choose an advisor before making the investment task in Part 1.

In Part 1, subjects received an endowment of 100 experimental tokens with an exchange rate of 0.05 from tokens to GBP. Subjects had to decide on splitting their endowment between two risky and one safe asset. To make the task less abstract and to simulate a financial decision-making context, we used loaded framing – we refer to risky assets as “investment opportunities”. Subjects were informed that the success or the failure of the two opportunities depends on the state of the economy. With probability 0.5 the economy grows fast and with probability 0.5 the economy grows slowly. If the economy grows fast, both opportunities succeed. If the economy develops slowly, both opportunities fail. Subjects can split their endowment between the two opportunities in any way they wish, and they can keep any part of the endowment in the safe asset, which is framed as keeping the money uninvested. Investment task in Part 1 is summarized in Table 4.1.

Table 4.1: Investment Task in Part 1

Economy State	Fast	Slow
Probability	0.5	0.5
Opportunity T	2.7	0
Opportunity P	1.9	0.2

In the fast-growth state, Opportunity T returns 2.7 times the investment, and opportunity P returns 1.9 times the investment. In the slow-growth state, subjects lose all their investment in the opportunity T and 0.8 of their investment in the opportunity P. That is, if the subject invests t into T and p into P, their earnings are given by:

$$Earning = \begin{cases} 100 + 1.7t + 0.9p & \text{in the fast-growth state} \\ 100 - t - 0.8p & \text{in the slow-growth state} \end{cases}$$

The investment decision is designed so that we can asses both portfolio riskiness, which can be a product of idiosyncratic preference, and the objective quality of a portfolio. In Specifically, we evaluate the objective quality of a given portfolio (t, p) by checking whether there exists an alternative portfolio (t', p') that first-order stochastically dominates it. Rather than offering participants a simple choice between two lotteries, we use a more complex setup involving two risky assets and one safe asset. This design increases decision complexity, making it more reasonable for subjects to seek or rely on financial advice. In our design, any portfolio (t, p) with $p > 0$ is first order stochastically dominated by any portfolio $(t', 0)$ for $t' \in [t + \frac{9}{17}p, t + \frac{4}{5}p]$. In other words, because splitting funds between the two risky assets offers no true diversification benefit, the optimal strategy is to allocate the endowment between the asset with higher expected value, Opportunity T, and the safe asset.

Importantly, subjects were required to answer a control question to confirm their understanding of the correlation between Opportunity T and Opportunity P before proceeding with the experiment.[1] This ensures that any investment in opportunity P is not due to a misunderstanding of the payoff structure, but rather to a failure to recognize the optimal decision given that structure. Previous research documents a tendency among economic agents to engage in naive diversification – allocating funds across highly correlated assets in the mistaken belief that doing so reduces risk (Benartzi and Thaler, 1999). Accordingly, we expect that at least some subjects will erroneously allocate part of their endowment to Opportunity P.

[1] Question 1: Suppose you have invested 40 tokens in opportunity T, 40 tokens in opportunity P, and left 20 tokens uninvested, is it possible that you earn money on your investment in opportunity T and lose money on your investment in opportunity P? Yes/No

Subjects in the control group made the investment decision by themselves. Then, they were asked to provide an explanation of their investment choice. Subjects in the treatment group had the opportunity to choose one out of a list of seven advisors who had more experience with the task. Before choosing the advisor, subjects were informed about the simulated earnings of advisors when performing the analogous task, along with their gender, education level, self-reported risk attitude and interest in finance and investing.[2] After choosing the advisor, subjects in the treatment group could read their advice which consisted of suggested portfolio, and a short explanation with additional comments. Next, subjects in the treatment group made their own investment decision, explained their choice and rated how helpful the advice was on a five-point scale. In order to eliminate order effect, we randomized the order of Opportunity T and Opportunity P for all subjects and also the order of advisors for subjects in the treatment group.

In Part 2, we used the BDM mechanism (Becker et al., 1964) to elicit certainty equivalents of subjects' investment portfolios in Part 1. Subjects had to decide the minimum price at which they were willing to sell the portfolio, which includes both their investment and the amount that they left uninvested. Each subject received a randomly generated offer between 0 and 275 tokens. If the reported minimum price to sell exceeds the randomly generated offer, subjects keep their investment. If the stated minimum price is below the randomly generated offer, subjects sell their investment, forgo the potential earnings from the portfolio and receive the randomly generated price. In Part 3, we used a short questionnaire to elicit subjects' risk preference, gender, educational level, whether they took finance-related courses and their experience and interest in investing. The risk elicitation measure is based on Dohmen et al. (2005, 2011).

4.3.2 Advice Elicitation

We elicited advice from seven members of social media Reddit subgroup r/UKPersonalFinance. There is an increasing growth in use of Reddit as a data source (Proferes et al., 2021). We focused on Reddit as according to the recent survey by Forbes (Egan, 2023), it is both the most

[2] Note that the advisors' chosen and advised portfolios are distinct –simulated earnings refer to the earnings of the portfolio advisors have chosen themselves, not to the one which they had advised. We provide more details on advice elicitation procedure in Subsection 4.3.2.

popular and the most trusted social media for seeking financial advice among Gen Zers. Indeed, the main advantage of eliciting advice from Reddit is that we could target subjects with high interest in financial matters or investment whose social media activity is likely to affect real-life investment decisions. Reddit has specific communities like r/UKPersonalFinance, r/Investing, r/FinancialIndependence, and r/Cryptocurrency that attract users who are interested and often experienced in financial matters. Users in these subreddits are likely to provide better advice in the financial task than traditional online subject pools such as Prolific and Mechanical Turk.

Before giving advice, advisors were given 2 minutes to practice the same investment task that was given to subjects. After the practice phase, advisors performed the investment task for one more round. The expected payoff of their decision in the last round was then displayed to subjects in the treatment group as “simulated earning", and in our analysis, it is used as a proxy for real-life historical returns.

After completing the investment task themselves, advisors were asked to provide advice to future participants. The advice took the following form. First, advisors needed to suggest how much to invest in Opportunity T and Opportunity P. This advice could have been distinct from their chosen portfolio. Second, advisors were asked to explain the reasoning behind their advice and provide additional suggestions. Finally, the advisors completed a short survey on their gender, educational level, risk attitude and whether they are interested in finance and investing. Advisors were informed that the expected value of their final portfolio in the practice round and the responses to the survey will be displayed to the subjects in the treatment group. To incentivize thoughtful advice, we implemented a reward scheme: two advisors were selected via lottery to receive a prize of 40 GBP each. Advisors earned lottery tickets based on feedbacks from treated subjects - each "useful" rating generated one ticket, while a "very useful" rating generated two.

4.3.3 Procedure

The experiments were run online via Prolific in October 2024 and were programmed using OTree. In total, 358 UK-based subjects were recruited. 178 subjects were randomly assigned to the control group and 180 were randomly assigned to the treatment. The sample is gender balanced. Subjects were paid 1.5 GBP participation fee together with their earnings in the investment tasks. The experimental tokens were converted to GBP at the exchange rate of 1 token = 0.05 GBP for final payment. Average earnings were 9.26 GBP including the participation fee. An experimental session took approximately 10 minutes. As for the advice elicitation, we received 7 full responses via Reddit subgroup r/UKPersonalFinance.

4.3.4 Hypotheses

The experiment examines the impact of advisor selection and financial advice on investment behavior, and we constructed three hypotheses to test the effects of advice selection on both the quantity and quality of investment decisions, as well as on the subjective welfare of subjects.

We hypothesize that subjects in the treatment group might benefit from receiving advice from more experienced advisors, and advice may improve the quality of investment decisions by helping subjects in the treatment group identify the stochastically dominated asset. Thus, we state the following three hypothesis.[3]

Hypothesis 1 ***Advice improves chosen portfolios' quality.***
(a) Subjects in the advice treatment group will allocate a <u>*lower*</u> *share of their investment to the dominated asset than those in the control group, indicating higher investment quality when advice is used. (b) Subjects in the advice treatment group invest* <u>*less*</u> *in the dominated asset. (c) Subjects in the advice treatment group are* <u>*less*</u> *likely to choose a dominated portfolio.*

We speculate that subjects tend to pick advisors with high simulated earnings. While advisors with higher simulated earnings could have made a good investment decision, they are also likely to choose portfolios with high exposure to risk. Consequently, advice from such advisors

[3] Hypothesis 1a, 2a, and 3 were preregistered, and Hypothesis 1b, 1c, 2b were added as to allow for different measurement of underlying concepts of riskiness and objective quality. For example, consider two portfolios $(t, p) = (60, 40)$, $(t', p') = (30, 30)$. We consider three ways of comparing the quality of portfolios. The first way is to compare share of the money invested in the dominated asset - then the first portfolio in which the subject invested $1/3$ in the asset p is of a higher quality than the second portfolio in which the subject invested $1/2$ in the asset p. The second way is to compare the absolute amounts invested in the dominated asset. Then the second portfolio is of higher quality than the first one. Finally, we can remain agnostic about such comparisons and only determine if the subject invests anything in the dominated asset. The three measurements correspond to Hypothesis 1.a, 1.b, and 1.c respectively. Similarly, consider two portfolios $(t, p) = (90, 0)$, $(t', p') = (0, 100)$. If we consider the total amount invested in risky assets as the measure of riskiness of portfolio, we would conclude that the first portfolio is safer than the second one. However, if we consider the worst-case-scenario payoff, then the second portfolio is safer.

might lead to more risk-taking behavior. As already observed by Apesteguia et al. (2020) and Schwerter (2024), information on the success of the investment of other people increases one's own risk taking. The presence of financial advice may increase the level of risk-taking among subjects. Specifically, we hypothesize that:

Hypothesis 2 ***Advice increases subjects' exposure to risk.***
(a) The total amount invested will be higher in the advice treatment group compared to the control group. (b) The low-growth state payoff will be lower in the advice treatment group compared to the control group, reflecting a greater propensity to risk when subjects had the opportunity to select an advisor.

Receiving advice may enhance subjects' subjective valuation of their portfolios as they might be more confident and assured in their decision (Soll et al., 2022), especially when the advice is from more experienced experts. Advice may also help subjects in the treatment group understand the task better, which may lead to better investment choice and a higher subjective valuation on the portfolio. Specifically, we hypothesize:

Hypothesis 3 ***Advice improves subjects' welfare.***
The certainty equivalent that subjects assign to their portfolios will be higher in the advice treatment group than in the control group.

4.4 Results

The results are structured as follows. First, we discuss the effects of advice on investment choice and portfolio structure. Then, we look at the effects of advice on earnings. Next, we check how participants selected the advisor and whether the advice was followed. In the end, we analyze the effects of advice on subjects' welfare.

4.4.1 Effects of Advice on Investment Choice

The first question we address, is whether advice affected the objective quality of the portfolios. Figure 4.1 shows the average investment choices between the two groups. We find evidence that opportunity to choose advice from more experienced subjects enhances the objective quality

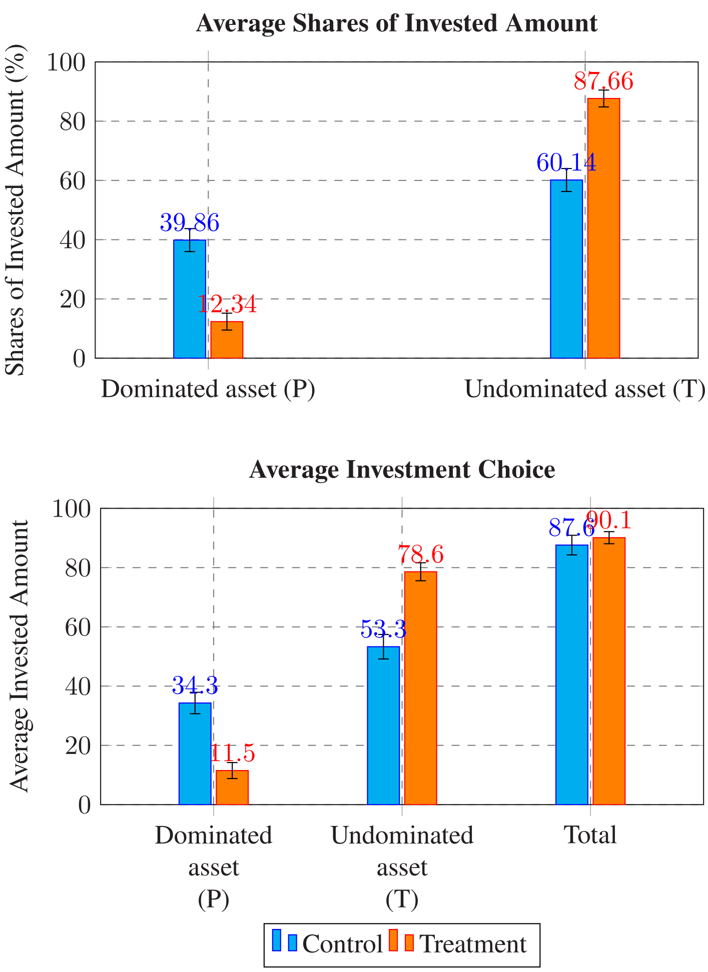


Figure 4.1: Average share and average amount invested. Error bars represent 95% confidence intervals.

of investment decisions. As depicted in Figure 4.1 and detailed in Table 4.2, both the average share and the average amount invested in the dominated option, Opportunity P, are significantly lower in the advice group compared to the control group (12.34% vs. 39.86%, 11.5 tokens vs. 34.3 tokens, $p < 0.001$, two-sided t-test). This impact is evident across both the extensive and intensive margins. Specifically, Figure 4.2 shows that 60.5% of subjects in the advice group allocated no funds to the dominated option, compared to only 17.4% in the control group ($p < 0.001, \chi^2(1, N = 358) = 69.94$). Furthermore, even among those subjects who did invest in the dominated opportunity, the amount invested was smaller under the treatment condition than in the control group.[4] We interpret subjects' tendency to invest part of the endowment in the dominated opportunity as naive diversification. Indeed, in the explanation of their choices, subjects who decided to invest some of the amount in Opportunity P reported "going for safety"

[4] 41.52 and 29.06 tokens invested in p, and 47.45% and 31.28% of total investment allocated to p by subjects who allocated any tokens to p in control and treatment group respectively. Both differences are significant with chi-squared test p-values below 0.001.

or "hedging the bets". Overall, we find that advice positively affects objective portfolio quality independently from the chosen metric.

Table 4.2: Average Investment Choice

	Control $(n = 178)$	Treatment $(n = 180)$
Investment in dominated asset (P)	34.3	11.5***
Investment in undominated asset (T)	53.3	78.6***
Total investment	87.6	90.1
Share invested in undominated asset (T)	0.60	0.88***
Share not invested in dominated asset (P)	0.17	0.61***

Notes: *** denote significant differences from the control group at 1% level, based on two-sided t-tests.

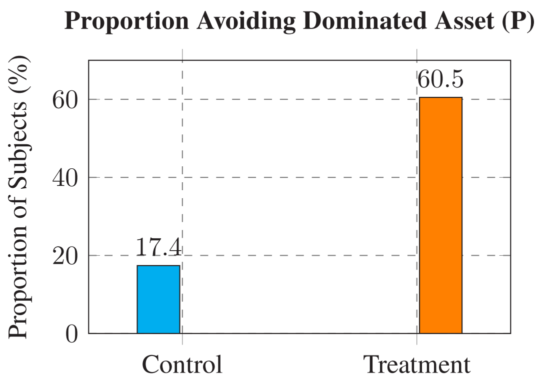


Figure 4.2: Proportion of subjects avoiding the dominated opportunity in the control and treatment groups. Error bars omitted for clarity.

Result 1. Consistent with Hypotheses 1a, 1b, 1c, subjects in the advice treatment group allocated a smaller share of their investment to the dominated option and invested a lower absolute amount compared to those in the control group. Moreover, subjects in the treatment group were significantly less likely to invest any tokens in the dominated option, both findings indicating that advice helps improve investment quality.

Second, we are interested in whether the access to advice affects investment size. We find that subjects in the treatment group tended to reallocate the tokens uninvested in Opportunity P directly to Opportunity T. Consequently, the average amount invested in the undominated option, Opportunity T, was significantly higher in the advice group than in the control group (78.6 tokens vs. 53.3 tokens, $p < 0.001$, two-sided t-test). However, the investment size did not significantly change (90.1 tokens vs. 87.6 tokens, $p = 0.21$, two-sided t-test). This absence of a significant effect can be partially attributed to the fact that a substantial portion of participants chose to invest their entire endowment. Moreover, this propensity was more pronounced in the control group, where 67.98% of subjects invested their entire endowment, compared to 59.44% in the treatment group ($p < 0.1, \chi^2(1, N = 358) = 2.82$). Yet a higher reluctance to invest entire endowment was counterbalanced by the intensive margin – subjects who did not invest the entire endowment, invested on average, 14.23 tokens more under treatment than under control ($p < 0.001$, two-sided t-test). Overall, the two effects cancel out.

Result 2. The total amount invested was not statistically different between the treatment group and the control group.

These results remain robust after controlling for demographic factors, including age, gender, education level, interest in finance, and prior education in finance. The corresponding regression analyses are presented in Appendix C.2.3.1.

4.4.2 Effects of Advice on Earnings

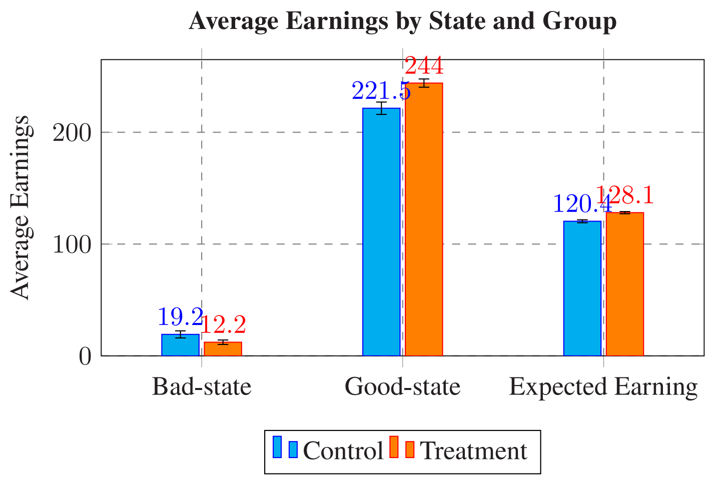


Figure 4.3: Error bars represent 95% confidence intervals for average earnings in different states.

We are also interested in how advice affects the distribution of earnings between states. Advice improves good-state (fast economic-growth) earnings and expected earnings. As illustrated in Figure 4.3, subjects in the treatment group earn 22.5 tokens more than subjects in the control group in the good state and the difference is statistically significant ($p < 0.001$, two-sided t-test). In terms of expected earnings, this difference translates to approximately 8 tokens more than their counterparts in the control group, with this difference also being statistically significant

($p < 0.001$, two-sided t-test). If we measure portfolio safety by earnings in the bad state (low economic-growth), we can see that advice increases the downside risk of the portfolio. As presented in Table 4.3 and Figure 4.3, the average earning in the bad state is significantly lower in the advice group compared to the control group (12.2 tokens vs 19.2 tokens, $p < 0.001$, two-sided t-test). These results are further confirmed by regression analysis presented in the Appendix C.2.3.2.

Table 4.3: Average Investment Earnings

	Control $(n = 178)$	Treatment $(n = 180)$
Bad-state earning	19.2	12.2***
Good-state earning	221.5	244***
Expected earning	120.4	128.1***

Notes: *** denotes significant differences from the control group at 1% level, based on two-sided t-tests.

Result 3. Consistent with Hypothesis 2b, the low-growth state payoff was lower in the treatment group compared to the control group, reflecting a greater propensity to risk when subjects had the opportunity to select an advisor.

4.4.3 Advisor Selection and Following Advice

We collected a total of seven responses that provided investment advice from the Reddit subgroup r/UKPersonalFinance. Subjects in the treatment group were presented with detailed information about the advisors, including their simulated earnings from the final practice round, gender, self-reported educational level, risk tolerance, and interest in finance and investing. To encourage the provision of meaningful advice, advisors were incentivized through a reward structure based on ratings provided by subjects in the treatment group. The order in which advisors were displayed to subjects was randomized to mitigate any ordering effects on advisor selection. Comprehensive details regarding advisors and their respective advice are provided in Table B1 and Table B2 in the Appendix.

Advisors sourced from Reddit demonstrated better performance in the investment task compared to subjects in both the control and treatment groups. This disparity may be attributed to advisors' prior experience with finance and investing, as well as their opportunity to engage in learning through the practice rounds. As illustrated in Table 4.4, five out of seven advisors recommended against investing in the dominated option. Among these five advisors, three explicitly explained the dominance relationship between the two options in their advice (see detailed advice in Table B2 in the Appendix). Notably, the advisor who achieved the highest simulated earnings in the final practice round was selected most frequently by subjects. Specifically, 52.78% of subjects in the treatment group chose the top-earning advisor, and slightly more than half of those who selected this advisor followed her recommendations. Average rating for each advisor can be found in Figure B3 in the Appendix.

Table 4.4: The Distribution of Advisor Selection

Advisor	Adv. P	Adv. T	Sim. Earn.	Risk Tol.	Chosen (%)	Advice Followed (%)
1	0	100	135.0	Low	95 (52.78%)	52 (54.74%)
2	0	80	128.0	Medium	41 (22.78%)	17 (41.46%)
3	0	80	128.0	Medium	17 (9.44%)	12 (70.59%)
4	35	65	124.5	Medium	8 (4.44%)	6 (75.00%)
5	0	50	117.5	High	5 (2.78%)	3 (60.00%)
6	0	50	117.5	High	5 (2.78%)	0 (0.00%)
7	34	33	113.3	Low	9 (5.00%)	3 (33.33%)

Notes: This table shows the distribution of advisor selection and the proportion of subjects who followed both advice from their chosen advisor. “Adv. P” and “Adv. T” refer to the advisor’s recommended investments in P and T. “Sim. Earn.” refers to the advisor’s simulated earning from the last practice round. “Risk Tol.” denotes the advisor’s indicated risk tolerance.

Strikingly, the key factor which subjects took into account when deciding on their advisor choice is simulated earnings. The majority of the subjects chose to receive the advice from the highest-earning advisor, and almost 85% chose one of the top 3 earners. The second consideration of the subjects was aligning the risk preferences of the advisor with their own risk preferences. As depicted in Figure 4.4 subjects who decided to receive advice from advisors with self-reported medium or high risk-tolerance reported on average almost 1 unit (on an 11-unit scale) higher risk-tolerance both in general and in financial matters, compared to subjects who chose low-risk-tolerant advisors ($p < 0.05$, two-sided t-test).

The intuition that simulated earnings were the primary factor in advisor selection, while alignment in risk preferences also played a role, is supported by an analysis of advisor choice

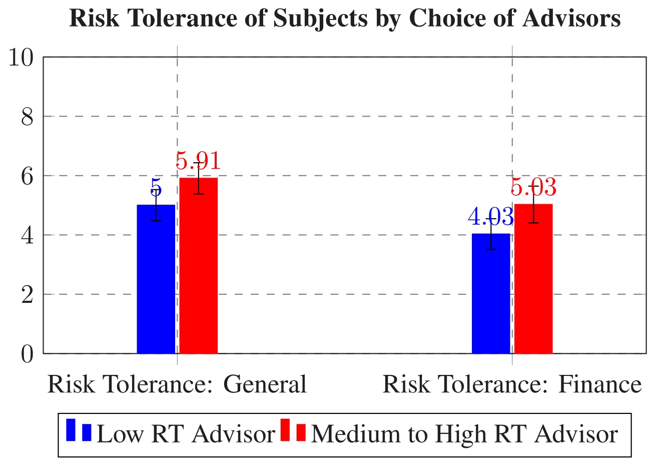


Figure 4.4: Average self-reported risk tolerance in general and in financial matters for treated subjects who chose a low risk-tolerant advisor ($N = 104$) and medium to high risk-tolerant advisor ($N = 76$).

using McFadden's conditional logit model (McFadden, 1984). Table 4.5 presents the estimation results for four specifications which differ in the way of capturing the effect of simulated earnings. Specification (1) includes advisor-specific dummy variables (with advisor 1 being the default choice) so that the effect of simulated earnings is captured only through the order of advisors. Specification (2) is analogous but pools the dummies for Advisors 2-4. Specifications (3) and (4) incorporate simulated earnings directly as a covariate, with Specification (4) additionally including the pooled dummy for Advisors 2–4.[5] We additionally include measures of homophily between subjects and advisors. Homophily in gender is modeled as a binary variable which takes the value of 1 if the subject is of the same gender as the advisor. To compute homophily in risk tolerance, we split subjects into three categories analogous to those applied to the advisors: subjects who reported general risk tolerance of 4 or less are classified as having low risk tolerance and those who reported general risk tolerance of 7 or more are classified as having high risk tolerance. Other subjects are assigned to medium risk tolerance category. Homophily in risk tolerance takes the value of 1 if both the subject and the advisor belong to the same class of risk tolerance, and takes the value of 0 otherwise.

We consistently report a positive effect of high simulated earnings on the likelihood of being chosen, regardless of whether the earnings are captured by top-earning advisor dummy or included directly as a variable. Moreover, in three out of four specifications (1,2,4), homophily

[5] We do not include any other advisor-level variables due to low variance in other advisor characteristics and challenges that it would pose to interpretation of parameters: for example, the only female are top-2 earning advisors and the only advisor declaring education above bachelor level is the least-earner.

in risk tolerance has a significantly positive effect on the likelihood of advisor being chosen. This effect emerges despite the risk tolerance information being elicited through an unincentivized survey, and relative crude method of classification of advisors into three groups.

Table 4.5: Estimation of McFadden's Choice Model for the Choice of Advisor

	(1)	(2)	(3)	(4)
Homophily in RT	1.01***	1.21***	0.26	0.84**
	(3.52)	(5.13)	(1.31)	(3.19)
Homophily in Gender	0.18	0.10	0.17	0.13
	(1.03)	(0.61)	(1.04)	(0.82)
Simulated Earnings			0.17***	0.09***
			(10.75)	(3.34)
Advisor $\neq$ 1		-2.42***		-1.28***
		(-12.10)		(-3.43)
Advisor 2 (cons)	-1.49***			
	(-5.51)			
Advisor 3 (cons)	-2.38***			
	(-7.25)			
Advisor 4 (cons)	-3.14***			
	(-7.52)			
Advisor 5 (cons)	-3.17***			
	(-6.62)			
Advisor 6 (cons)	-3.17***			
	(-6.62)			
Advisor 7 (cons)	-2.36***			
	(-6.76)			
N	1260	1260	1260	1260

Notes: Each column reports coefficients from a conditional logit (McFadden's choice) model. The dependent variable is the choice of advisor among 7 alternatives. t-statistics are reported in parentheses.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Notably, in our experiment, advisors' self-reported risk tolerance proved to be a poor signal for the actual riskiness of their recommendations. Among the advisors who suggested investing in dominated portfolios (Advisors 1, 2, 3, 5, and 6), the advisor who identified as having low risk tolerance recommended the most risky portfolio. Conversely, two advisors who reported high risk tolerance advised selecting the least risky portfolios. This discrepancy poses a question: did subjects modify the advised portfolios to better align with their own risk preferences?

A substantial proportion of subjects in the treatment group followed the advice provided by their selected advisors. As shown in Table 4.6, 51.67% of subjects followed both pieces of advice, 65.56% followed the investment advice regarding the dominated option P, and 55.56% followed advice on option T. To examine the relationship between advisor recommendations and subjects' investment decisions, we verify Spearman's rank between the advised and chosen portfolios. The analysis shows statistically significant and positive associations between advisor recommendations and investment choices. Specifically, subjects were influenced by advice for both option P ($\rho = 0.489, p < 0.001, n = 180$) and option T ($\rho = 0.536, p < 0.001, n = 180$), with a slightly stronger correlation observed for the undominated option T. The relationship remains consistent when analyzing total advice and total investment ($\rho = 0.528, p < 0.001, n = 180$).

Table 4.6: Proportion of Subjects Following Advice in the Treatment Group

	Percentage of Subjects
Followed advice in P	65.56%
Followed advice in T	55.56%
Followed both advice	51.67%

A possible problem with interpreting the numbers in Table 4.6 is that some of the advised portfolios are also popular among subjects in the control group (see Table B3 in Appendix C). Consequently, it is not immediately clear whether portfolio choices in the treatment group were driven by the received advice or whether they simply reflect general preferences for certain popular portfolios.

Subjects in the treatment group are almost equally split between those who completely followed the advice, and those who did adjust their portfolios. As expected, subjects who adjusted the portfolios tended to decrease the investment in the opportunity T, presumably, in order to decrease riskiness of the portfolio. This intuition is corroborated by the text analysis of explanations of investment choices in the treatment group. Our findings reveal that 51.1% of subjects reported trusting their advisor and fully following the provided advice. However, deviations from the advised portfolio were often driven by individual risk considerations. Specifically, 7.8% of subjects stated that they agreed with their advisor's recommendation but opted to invest less in T, reflecting a preference for lower risk exposure. Additionally, 4% of subjects mentioned that while they trusted their advisor, they preferred to retain a greater proportion of their endowment uninvested. Conversely, another 4% of subjects expressed a willingness to take on greater risk, investing more in T than was advised. Typically, subjects who decided not to follow the advice increased their investment in the opportunity P at the cost of opportunity T. Overall, as we show in Table 4.7, the deviations resulted in significantly lower returns, without significantly improving the worst-case scenario payoff.

Table 4.7: Average Differences Between Advised and Chosen Portfolios

Δ Dominated Asset (P)	8.20***
Δ Undominated Asset (T)	-7.24***
Δ Total Investment	-0.96
Δ Expected Return	-2.12***
Δ Bad-state Payoff	0.68

Notes: This table shows average differences between advised portfolios and chosen portfolios for the treated subjects ($n = 180$). *** indicates significance at 1% level based on two-sided t-tests.

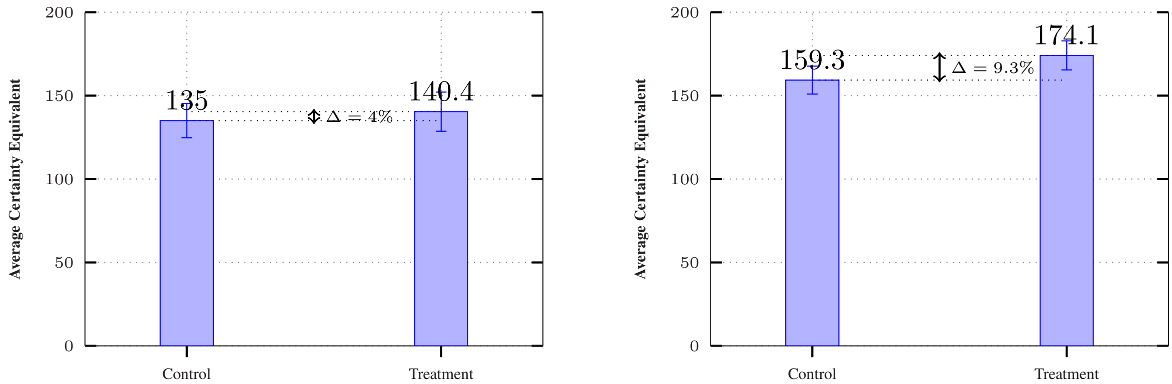
Even though the subjects who deviated from advice tended to perform worse than those who followed the advice, they still performed better than subjects in the control group. They invested significantly less in the dominated asset both in terms of shares and absolute value, and are less likely to choose a dominated portfolio. In particular, treated subjects who did not follow the advice invested on average 14.16 tokens less in the dominated asset, which is equivalent to them holding 18.48 percentage points lower share of dominated asset, as compared to untreated subjects. Both differences are significant at 1% level (two sided t-test). The proportion of subjects who held undominated portfolio is 11.14% higher among the treated subjects who did not follow the advice than the untreated subjects, a difference being significant at 5% level.

Subjects in the treatment group were asked to evaluate the perceived helpfulness of the selected advice on a scale from 1 to 5, where 1 indicated "not helpful at all" and 5 represented "very helpful". This evaluation was conducted prior to the realization of the investment outcome. Overall, subjects rated the advice favorably, with an average helpfulness score of 4.12. Those who explained the dominance relationship were rated being slightly more helpful than those who didn't explain the dominance relationship (4.16 vs 3.86, one-sided t-test, $p < 0.1$). Average helpfulness rating of each advisor can be found in Table B3 in the Appendix.

4.4.4 Effects of Advice on Welfare

Our analysis in Section 4.4.1 demonstrates that subjects who selected advisor were less likely to choose a dominated portfolio and, on average, allocated fewer tokens to the dominated asset.[6] However, this finding alone does not allow us to directly conclude that exposure to advice improves subjects' welfare. A key consideration is the trade-off between risk and return. If portfolio risk, measured by the worst-case-scenario payoff, rises, it is possible that some subjects would be better off selecting a dominated but relatively safer portfolio. In such cases, avoiding dominated portfolios does not necessarily correspond to improved welfare. However, choosing more risky portfolios can be a sign of diminished cognitive uncertainty and higher confidence in the choices made (Enke and Graeber, 2023).

To address this issue, we conduct two exercises. First, we use the BDM mechanism to elicit certainty equivalents of the chosen portfolios and compare them across treatments. Second, we simulate the welfare of the subjects.



Entire Sample ($N = 358$) Rationalisable Sample ($N = 232$)

Figure 4.5: The figure depicts certainty equivalents elicited using BDM mechanism for control (color) and treatment (color). Panel on the left depicts the entire sample ($N = 358$), and panel on the right depicts only those subjects whose choices could be rationalized by expected utility theory ($N = 232$).

[6] The latter statement is true even if we focus only on the intensive margin, and look only at the subjects who invested anything in the dominated portfolio. Subjects who invested in the dominated asset in the treatment group, invested in 29 tokens, compared to 41 in the control group, a difference significant at a 1% level.

Figure 4.5 shows that subjects in the treatment group reported on average 4% higher certainty equivalent than those in the control group, however, the difference is not statistically significant.[7] We attribute the modest effect size primarily to the relatively high cognitive demands of the BDM mechanism, which may have led many participants to struggle with accurately valuing their portfolios. In particular, some responses may have been anchored by the example used to explain the BDM procedure. When we restrict the analysis to subjects whose reported certainty equivalents are consistent with standard expected utility theory—specifically, those who report a value no lower than the guaranteed 100-token payoff and no higher than the maximum possible payoff—the average treatment effect rises to nearly 10% and becomes statistically significant at 1% level. We show in Appendix C.2.4 that this result remains robust when controlling for participants' education, age, gender, risk aversion, risk attitudes, and prior experience with finance or investing.

While studying elicited certainty equivalents of the portfolios yields some evidence that advice has positive effects on subjects' welfare, the fact that the effect is particularly strong for individuals whose behavior can be rationalized by expected utility raises some doubts. In particular, it is possible that the remaining subjects are precisely those who are the most exposed to potential negative effects of the advice. To address this concern, we additionally run a few welfare simulations in Appendix C.2.4 , in which we impose different assumptions on the nature of subjects' risk preferences. We consistently find that, while a small share of subjects might have been harmed by the exposure to advice, subjects are typically better-off when receiving advice.

Result 4. The certainty equivalents are not statistically different between the treatment and control groups. However, among individuals whose preferences can be explained by expected utility, the welfare of treated individuals is significantly higher.

[7] Although we allowed unlimited choice of declared valuations when implementing BDM mechanism, we censor the data by applying the highest transfer possible (275) as the cap, in order to avoid few individuals who declared exaggerated valuations, presumably, as a way of never selling the portfolio. Uncensored data results suggest a higher difference between the certainty equivalents of treatment and control.

4.5 Conclusion

Our findings show the dual effects of advice on financial decision-making. Subjects who could choose advisors invested less in the stochastically dominated asset, demonstrating improved investment quality. However, they also exhibited higher exposure to downside risk. The majority of the subjects followed the advice of the advisors and reported that the advice was helpful. Notably, most subjects picked the advisor with the highest simulated earnings. This result indicates that perceived past success strongly influences advisor selection. While many followed their chosen advisor's recommendations, others made adjustments—often reducing risk but at the expense of potential returns. Beyond investment choices, our welfare analysis suggests that individuals who could choose their advisor valued their portfolios more highly, particularly among those whose decisions were aligned with expected utility theory.

Notably, our framework is still a simplification of the reality of online financial advice. We find two promising avenues for future research. First, we restrict our subjects to choose and receive only one single piece of advice. In reality, at least some investors check the advice from multiple sources. On the one hand, it may help investors to explore the full extent of investment possibilities and ultimately make even better decisions. On the other hand, if the opinion leaders draw their opinion from the same source, abundance of advice may result in worse rather than better decision making (Yaniv et al., 2009). Moreover, abundance of advice may result in information overload, inefficiently postponing investment (Chervany and Dickson, 1974), or incentivizing active trading (Heimer and Simon, 2015). Second, a large portion of online financial advice do not focus on improving investors' decision-making but rather on influencing their habits, beliefs, and preferences (Choi, 2022). However, with our design, we are unable to verify if subjects preferences are actually affected by exposure to advice.

A Appendix for Study I

A.1 Descriptive Statistics

A.1.1 Sample Statistics

Table A.1: Descriptive Statistics of Survey Sample

	Whole	US	China	Germany	Sweden	New Zealand	South Korea	South Africa	Brazil
Age	38.96	41.55	34.87	43.04	41.53	40.48	39.02	35.4	36.96
Age group (%)									
18-24	0.17	0.16	0.21	0.11	0.15	0.16	0.15	0.24	0.19
25-34	0.24	0.20	0.29	0.18	0.20	0.20	0.24	0.31	0.28
35-44	0.24	0.20	0.30	0.23	0.21	0.23	0.26	0.18	0.24
45-54	0.20	0.20	0.17	0.25	0.22	0.22	0.22	0.15	0.18
55-65	0.16	0.23	0.04	0.24	0.23	0.19	0.13	0.12	0.12
Female	0.50	0.50	0.49	0.49	0.51	0.55	0.49	0.50	0.51
Married	0.58	0.51	0.71	0.61	0.50	0.59	0.49	0.50	0.57
College edu.	0.64	0.64	0.83	0.38	0.41	0.53	0.79	0.51	0.54
Employed	0.51	0.48	0.51	0.61	0.52	0.60	0.37	0.51	0.50
Self-employed	0.10	0.08	0.12	0.10	0.06	0.06	0.08	0.12	0.18
Student	0.08	0.05	0.09	0.06	0.12	0.07	0.11	0.11	0.06
Not employed	0.31	0.38	0.29	0.23	0.29	0.33	0.21	0.39	0.25
Household Size	3	2.76	3.38	2.40	2.5	3.11	3.26	3.91	3.44
Observations	17728	5417	4567	1200	1095	2063	1082	1104	1200

A.1.2 Likelihood of Wearing Face Masks

Table A.2: Average Likelihood of Wearing Face Masks by Region

Region	Before Corona		During Lockdown		After Corona	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Whole Sample	6.63	3.58	9.52	3.73	8.67	3.76
Whole US Sample	3.79	2.34	5.52	1.98	5.24	1.97
California	3.79	2.29	5.55	1.94	5.29	1.91
Texas	3.85	2.33	5.41	2.02	5.14	2.01
Florida	3.82	2.37	5.48	2.03	5.26	2.02
New York	3.79	2.39	5.60	1.98	5.30	2.00
Whole Chinese Sample	4.5	1.55	5.93	1.18	5.65	1.13
Wuhan, Hubei Province	4.56	1.55	5.83	1.19	5.69	1.11
Other Cities, Hubei Prov.	4.48	1.48	5.62	1.30	5.36	1.17
Guangdong Province	4.42	1.65	6.08	1.12	5.77	1.12
Henan Province	4.63	1.48	5.84	1.20	5.58	1.13
Beijing	4.43	1.55	6.06	1.12	5.71	1.12
Germany	2.74	2.07	5.42	2.00	4.48	2.05
Sweden	2.48	1.83	4.09	2.08	3.39	1.95
New Zealand	3.49	2.21	5.40	1.94	4.81	11.94
South Korea	4.63	1.78	6.22	1.22	5.77	1.30
South Africa	3.40	2.21	5.89	1.80	5.48	1.86
Brazil	3.73	2.32	6.28	1.64	5.90	1.76

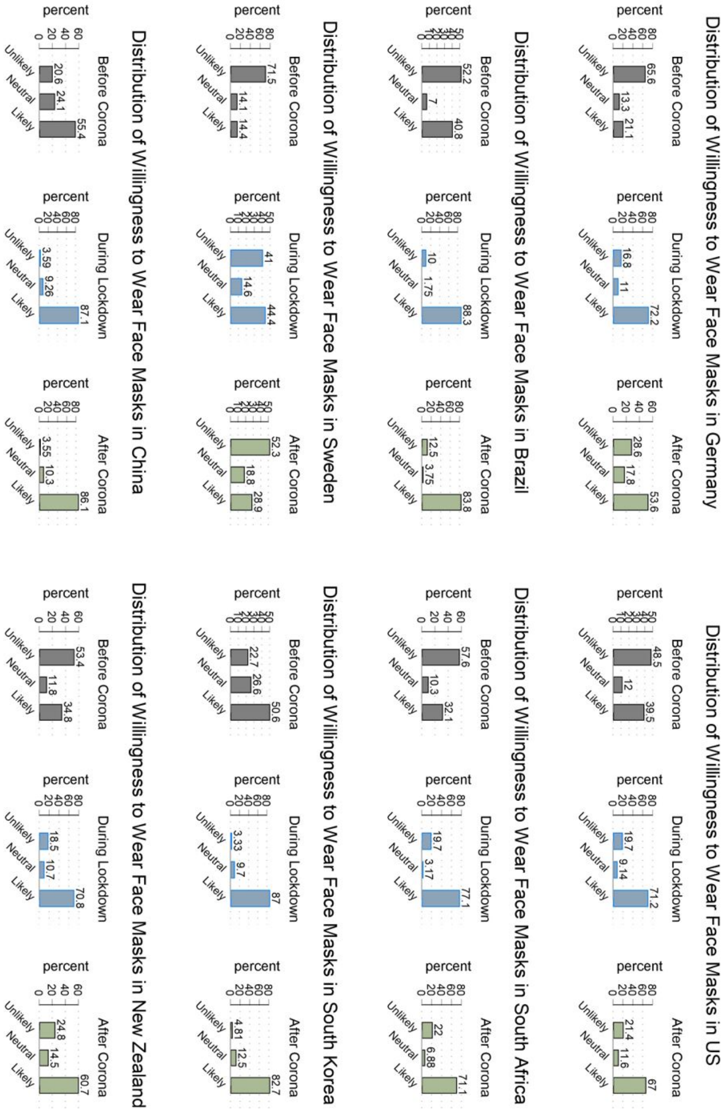


Figure A.1: The figure shows the percentage distribution of the likelihood of wearing face masks in time of sickness by time period and country. The bar "Likely" includes scales 5 to 7 and the bar "Unlikely" consists of scales 1 to 3. The bar "Neutral" represents scale 4 in the rating.

A.1.3 Frequency of Hand Washing Per Day

Table A.3: Average Frequency of Hand Washing Per Day by Region

Region	Before Corona		During Lockdown		After Corona	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Whole Sample	6.63	3.58	9.52	3.73	8.67	3.76
Whole US Sample	7.08	3.91	9.31	3.90	8.84	3.92
California	7.00	3.85	9.23	3.85	8.68	3.87
Texas	7.34	3.96	9.23	3.99	8.97	4.01
Florida	7.58	4.05	9.90	3.86	9.45	3.99
New York	7.02	3.79	9.47	3.83	8.85	3.78
Whole Chinese Sample	6.01	3.05	9.21	3.32	7.97	3.35
Wuhan, Hubei Province	6.16	3.19	9.25	3.34	8.31	3.43
Other Cities, Hubei Prov.	5.02	2.79	8.39	3.38	7.12	3.35
Guangdong Province	6.00	3.03	9.50	3.26	8.12	3.38
Henan Province	6.40	2.96	9.08	3.18	7.90	3.12
Beijing	5.98	3.09	9.38	3.40	8.05	3.41
Germany	6.36	3.30	8.66	3.64	7.83	3.45
Sweden	7.06	3.59	9.58	3.89	8.55	3.68
New Zealand	6.86	3.69	9.64	3.85	8.59	3.75
South Korea	5.81	3.31	8.84	3.54	8.10	3.56
South Africa	6.47	3.67	11.07	3.61	10.30	3.91
Brazil	7.30	3.67	11.43	3.40	10.73	3.67

A.1.4 Lockdown Interventions and Lockdown Length by Region

We used the following question to elicit lockdown interventions in the survey:

Which of the following **interventions** has your local government implemented during the strictest lockdown to contain the coronavirus?

⊡ Ban on dining in restaurants and bars

⊡ Closure of shopping malls

⊡ Ban on going to parks

⊡ Ban on going outside for leisure reasons or sports

⊡ Ban on traveling within the country for leisure reasons

⊡ Mandatory temperature/health checks when leaving your accommodation

⊡ Ban on religious gatherings

⊡ Ban on gatherings at home (e.g. visits from family, friends, etc.)

⊡ Ban on going out except for essential reasons (e.g. groceries shopping, doctor's visit, work, etc.)

⊡ Total ban on going outside

⊡ None of the above

Table A.4: Number of Reported Governmental Interventions and Perceived Lockdown Strictness

Region	Number of Bans	
	Mean	S.D.
Whole US Sample	4.74	2.99
California	5.13	3.06
Texas	4.16	2.85
Florida	4.38	2.95
New York	5.19	3.00
Whole Chinese Sample	6.67	3.66
Wuhan, Hubei Province	7.49	3.75
Other Cities, Hubei Prov.	5.70	4.24
Guangdong Province	6.46	3.40
Henan Province	6.87	3.62
Beijing	6.60	3.51
Germany	5.00	2.42
Sweden	1.02	1.48
New Zealand	6.55	2.32
South Korea	3.07	3.31
South Africa	7.62	2.35
Brazil	6.54	2.54

The number of self-reported governmental interventions is positively correlated with individual's perceived lockdown strictness (Spearman correlation coefficient = 0.36, $p < 0.01$)

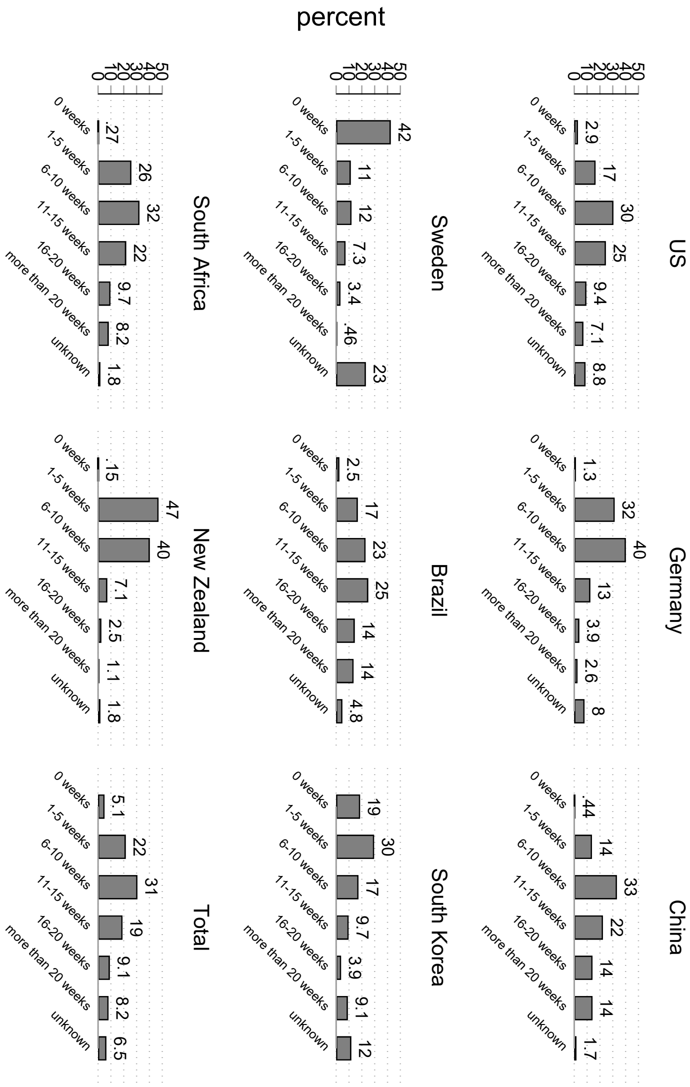


Figure A.2: Distribution of reported lockdown length by region

A.2 Additional Results

A.2.1 The Effects of Mandates of Wearing Face Masks in Public on Face Mask Habit

	(1)	(2)	(3)	(4)
	Short Run	Long Run	Short Run	Long Run
Mandatory mask policy	0.748***	0.607***	0.596***	0.477***
	(0.035)	(0.030)	(0.038)	(0.033)
Lockdown length:				
1-5 weeks	0.490***	0.487***	−0.036	0.074
	(0.082)	(0.072)	(0.083)	(0.073)
6-10 weeks	0.263***	0.398***	−0.184*	0.0365
	(0.080)	(0.070)	(0.081)	(0.072)
11-15 weeks	0.0623	0.288***	−0.329***	−0.0356
	(0.084)	(0.074)	(0.085)	(0.075)
16-20 weeks	−0.156	0.132	−0.401***	−0.079
	(0.092)	(0.081)	(0.092)	(0.082)
more than 20 weeks	−0.428***	−0.124	−0.617***	−0.287***
	(0.094)	(0.083)	(0.094)	(0.083)
Unknown	−0.071	0.024	−0.268**	−0.133
	(0.097)	(0.085)	(0.095)	(0.084)
Other intervention controls	No	No	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes
Observations	17728	17728	17728	17728
R^2	0.090	0.067	0.133	0.103

Table A.5: The effects of mask mandates on the change in the likelihood of wearing face masks when feeling sick. This table shows the random-effect models on the change of the likelihood of wearing face masks during sickness, as a function of whether face masks are mandatory in certain public areas during the lockdown. Columns 1 and 3 represent short-run change, and columns 2 and 4 represent expected long-run change. All regressions include age, gender, marital status, education level, employment status, financial stress level during lockdowns, risk attitude in general, risk attitude in health related issues, perceived health status, whether there are kids at home and whether there are elderly aged above 65 at home as controls. Columns 3 and 4 further controls for all the other reported interventions. Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01

A.2.2 Political Preferences and Change in the Likelihood of Wearing Face Masks Among US Participants

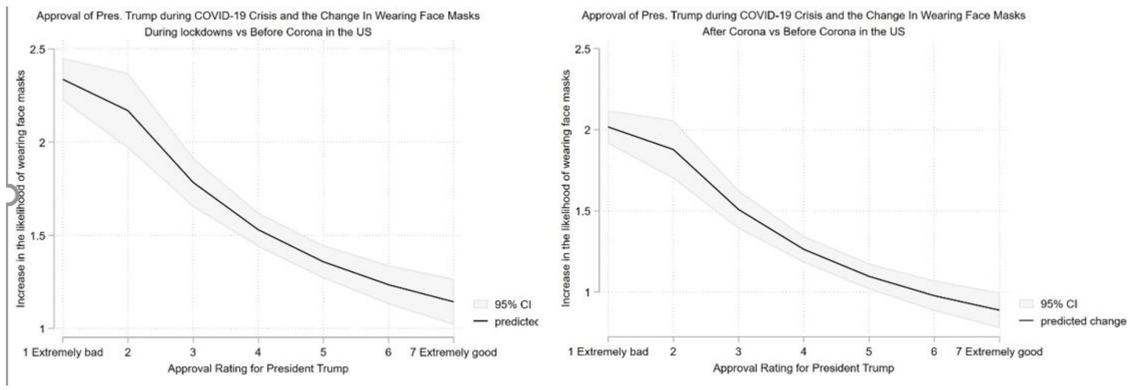


Figure A.3: The figure shows the results of polynomial fitted regressions on the US sample for the increase in the likelihood of wearing face masks during lockdown compared to before Corona (left panel), and expectations after Corona compared to before Corona (right panel), as a function of individual's approval of Trump's approach to dealing with the COVID-19 crisis. The shaded areas indicate 95% confidence intervals. The higher the approval of Trump's approach to the pandemic, the lower the increase in the likelihood of wearing face masks both during the lockdown and after Corona.

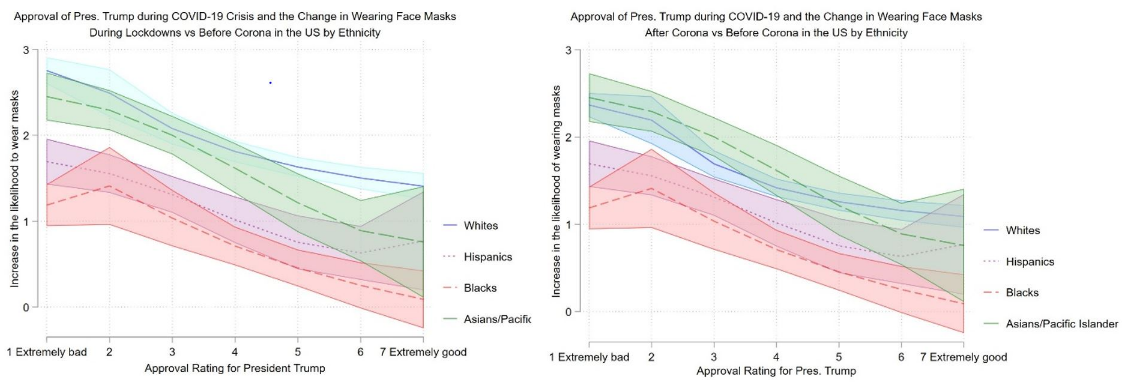


Figure A.4: Approval of Trump during COVID-19 and the change in wearing face masks. The figure shows the results of polynomial fitted regressions for the increase in the likelihood of wearing face masks during lockdown compared to before Corona (left panel), and expectations after Corona compared to before Corona (right panel), as a function of the individual's approval of Trump's approach to dealing with the COVID-19 crisis for different ethnicities in the US. The shaded areas in each case indicate 95% confidence intervals.

A.2.3 Political Preferences and Change in Hand Washing Frequency Among US Participants

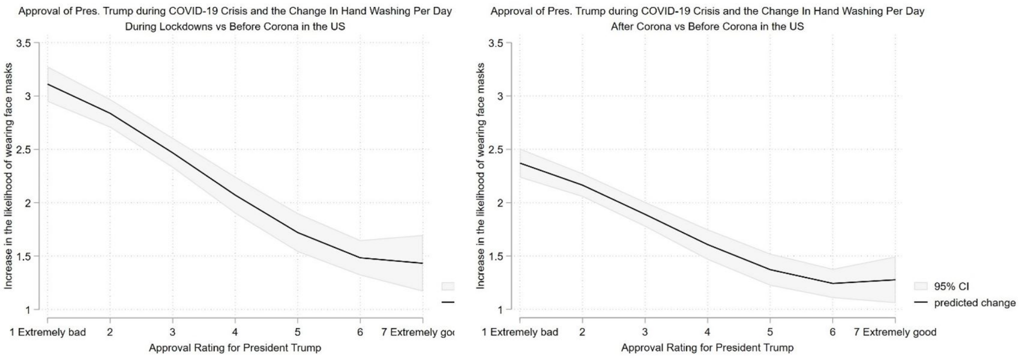


Figure A.5: The panel exhibits the polynomial fitted regression plots for the change in the frequency of hand washing, as a function of individual's approval for Trump's approach in dealing with the COVID-19 crisis for the US respondents.

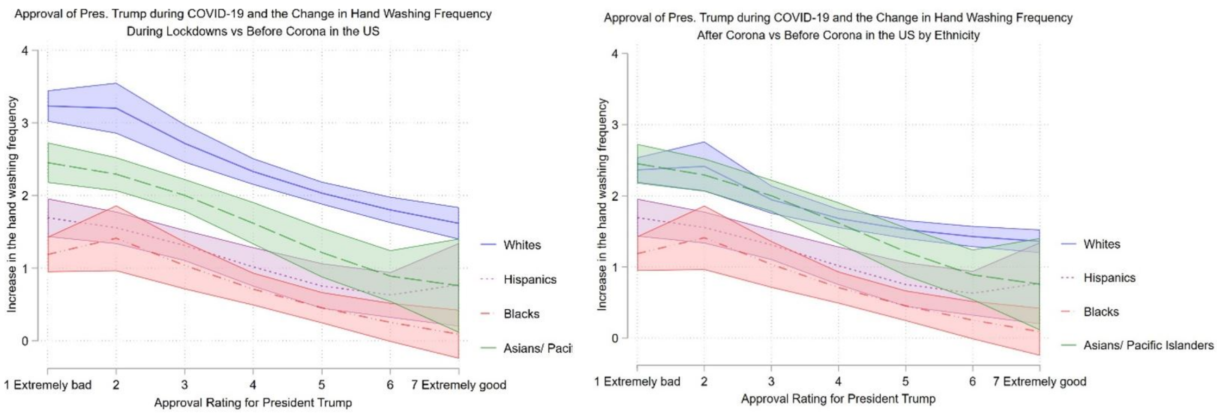


Figure A.6: The panel exhibits the polynomial fitted regression plots for the change in the frequency of hand washing, as a function of individual's approval for Trump's approach in dealing with the COVID-19 crisis for different ethnicities among US respondents. The shaded areas represent 95% confidence interval in each case.

A.2.4 Sentiment in Tweets

As a further analysis, we investigated the textual sentiments in tweets about hygiene habits. For this purpose, we used the NRC emotion lexicon to calculate sentiment scores measuring the extent of positive vs. negative emotions embedded in tweets (Mohammad and Turney, 2013). As shown in Figure A.7, there was a more positive sentiment towards hand washing throughout the entire observation period. In contrast, we found an increasingly negative sentiment towards face masks, in particular after the state-at-home period has ended. This indicates that wearing face masks might still be a controversial topic after the lockdowns despite a significant proportion of survey participants in the U.S. expecting to wear face masks when feeling sick after the pandemic.

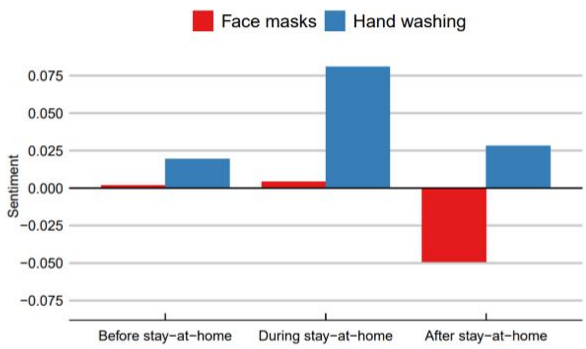
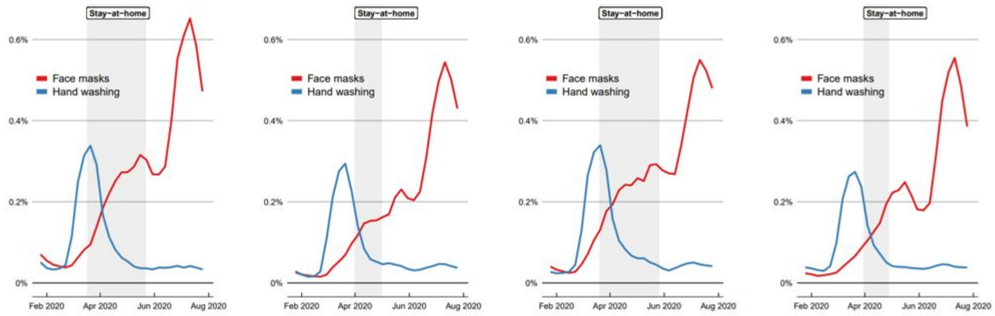


Figure A.7: Sentiment in hygiene tweets. Shown is the average sentiment of tweets referring to "Face Masks" and "Washing Hands" within four U.S. states (California, Florida, New York and Texas. Results are based on approximately 9.4 million Tweets. Stay-at-home order effective: CA 2020/03/19; NY 2020/03/22; TX 2020/04/02; FL 2020/04/03.)

A.2.5 Habits on Twitter and Google Trends Across Individual US States

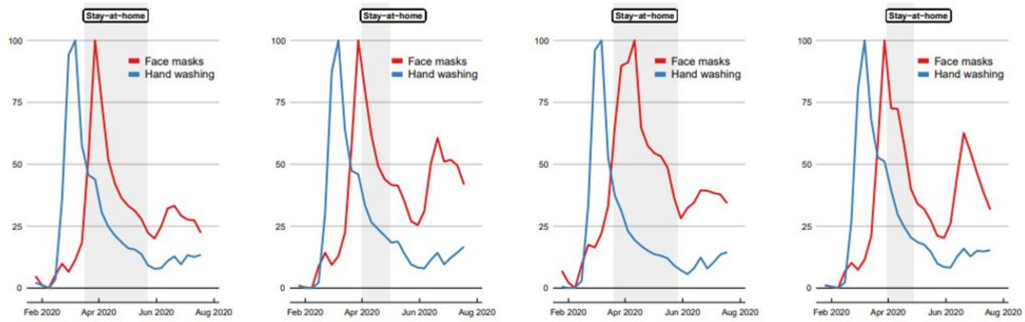
We also compared the habit trends for each of the four U.S. states individually (see Figure A.8). Here we find robust patterns for both hygiene habits across all four states.



(a) California, USA (b) Florida, USA (c) New York, USA (d) Texas, USA

Figure A.8: Hygiene habits on Twitter. The share of tweets referring to "Face Masks" and "Washing Hands" is visualized separately for (a) California, (b) Florida, (c) New York and (d) Texas.

As shown in Figure A.9, the patterns on Google Trends are robust across all four U.S. states, which is largely consistent with the Twitter analysis.



(a) California, USA (b) Florida, USA (c) New York, USA (d) Texas, USA

Figure A.9: Hygiene habits on Google Trends. Shown in Google Trends' search volume index for "Face Masks" and "Washing Hands" separately for (a)California, (b)Florida, (c)New York and (d)Texas. Results are based on approximately 9.4 million Tweets. Stay-at-home order effective: CA 2020/03/19; NY 2020/03/22; TX 2020/04/02; FL 2020/04/03.

A.3 Analysis of Tweets

A.3.1 Data Collection

We employed the Twitter API to collect a time series of random tweets from four U. S. states, namely, California, Florida, New York, and Texas. Since we are interested in how habits evolve over time, we did not restrict the crawler to any sets of predefined keywords but rather collected random samples of all publicly available English-speaking tweets. The four crawlers (one crawler per location) collected tweets in the timeframe between the last week of January 2020 (i. e., the week in which the WHO declared an emergency of international concern (WHO, 2020)) and end of July 2020, i. e., for an observation period of six months. The crawlers collected a large-scale tweet sample consisting of up to $1\,\%$ of all available public tweets in each of the four U. S. states.

To ensure computational feasibility and avoid sampling biases in our dataset, we generated equally sized random subsets of tweets from the raw data for each day in our observation period. Specifically, we implemented the following sampling process: (1) to reduce potentially confounding daytime and timezone effects, we randomly sampled an equal number of 500 tweets for each hour of each week in each U. S. state. (2) We excluded reply Tweets and retweets.[1] The sampling process yielded $500 \times 24 = 12000$ tweets per day for each of the four U. S. states. The total number of tweets is ≈ 9.4 million over a time period of six months.

A.3.2 Classification of Habits in Tweets Using Machine Learning

We make use of state-of-the-art methods from machine learning and natural language processing to predict whether individual tweets in our dataset refer to a certain habit. Yet standard supervised machine learning approaches for text classification are not readily applicable to our task as they would require training observations in the form of annotated tweets (i. e., habit labels for each individual tweet). The latter would be difficult to obtain through manual labeling as only a relatively small proportion of posts on Twitter refer to habits. To overcome these hurdles, we build upon recent advances in machine learning and learn to predict fine-grained habit labels

[1] Our analysis yields qualitatively identical findings if we additionally include reply tweets and retweets.

(e. g., *Face masks*, *Hand washing*) for tweets via *weak supervision* (Yao et al., 2020). Weak supervision is a branch of machine learning where noisy labels are used to provide supervision signals for labeling large amounts of training data (Hernández-González et al., 2016). As detailed in the following, this allows us to rapidly label tweets that can then be used as training data in state-of-the-art machine learning methods for text classification. Compared to alternative methods, weak supervision has two crucial advantages in our setting: (i) it significantly outperforms unsupervised learning approaches (e. g., topic modeling, keyword matching approaches) for fine-grained classification of tweets in terms of prediction performance (Yao et al., 2020); (ii) it alleviates the burden of obtaining hand-labeled data sets of tweets. Instead, weak supervision allows us to create high-quality labeled training data for machine learning in a rapid manner with minimal human supervision.

We generated high-quality labeled training data for machine learning as follows (see Yao et al. (2020) for methodological details): In a first step, we start to identity habit-related tweets based on a set of relevant keywords for each habit. For instance, for the habit *Face masks*, we search for all tweets containing words such as "face mask," "wear mask," "mask distancing," etc. In our analysis of habits on Twitter, we focus on the following six habits: (1) *Face masks*, (2) *Hand washing*, (3) *Teleworking & online studying*, (4) *Online video conferencing*, (5) *Digital gaming*, and (6) *Online streaming*. The full list of keywords for each habit is provided in Appendix A.3.3. In a second step, we conduct clustering-assisted manual word sense disambiguation on the keyword-identified tweets (Navigli, 2009). The rationale is that the keyword-identified tweets may be noisy, that is, the data may include tweets that contain habit-related keywords but do not show the pertinent meaning of the habit. To this end, we use the k-means clustering algorithm with Silhouette criterion to cluster the keyword-identified tweets for each habit. This results in 2–25 clusters per habit. Analogous to Yao et al. (2020), we then manually inspect five tweets randomly sampled from each cluster and assess whether the tweets in the cluster clearly refer to the habit. We find that all tweet clusters show the pertinent meaning of the corresponding habits. This implies that there is very little noise in the keyword-identified tweets and, thus, we do not remove any of the tweet clusters from the training data. Altogether, this intermediate clustering step ensures high-quality training data that can then be used as training data for machine learning.

Next, we use the created labeled data to train a deep neural network classifier and learn to predict whether or not individual Twitter messages belong to a certain habit. The input data for the training machine learning classifier are a vector representation of the keyword-identified tweets and the habit label (e. g., *Hand washing*). To create vector representations of tweets, we use neural language models in the form of the Universal Sentence Encoder (Cer et al., 2018). In a nutshell, the Universal Sentence Encoder encodes text into high dimensional vectors of fixed length that can be used for text classification. The main benefit of neural language models (compared to bag-of-words approaches) is that they leverage the strength of large-scale deep neural networks and are thus able to capture context, semantics, structure, and meaning (Jurafsky and Martin, 2020). In our deep neural network classifier, we treat the task of predicting habit labels for (vector representations of) tweets as a multi-label problem considering that one tweet may belong to multiple habits. A tweet may receive multiple labels if it discusses more than one habit such as in "wash your hands and wear a mask." In training, we use an equal number of $10{,}000$ keyword-identified Tweets for each habit as positive training instances. In addition, we randomly sample unlabeled tweets equal to the sum of labeled tweets and use them as negative training instances, i. e. with a label *Other*. In sum, for six habits, this results in a training dataset consisting of $120{,}000$ Tweets. We then follow common practice in machine learning to train the machine learning classifier (Hastie et al., 2009). We optimize the number of layers, the number of neurons per layer for each layer, and the learning rate via grid search. All hyperparameters are tuned using 10-fold cross validation.

After training the (weakly supervised) machine learning classifier, we evaluated the quality of the predictions based on human annotations. For this purpose, we randomly sampled 250 out-of-sample predictions for each of the seven habit labels. We then instructed[2] four students to label the tweets. The annotators worked independently of each other and were asked whether or not the individual tweets refer to one of the habits. A tweet is annotated with one (or multiple) habit categories if it directly refers to the defined habit, including sharing information and expressing opinions. If one tweet does not discuss any of the habits, it is labeled as *Other*. To assess the

[2] We conducted an initial test round with 100 (additional) random tweets to ensure that each student understands the annotation task. The annotations from this test round are not used to evaluate the prediction performance of the machine learning classifier.

agreement between annotators, we first divided the four annotators into two groups of two each. Each group of annotators were then asked to annotate a common set of 500 tweets. To this end, the annotators reached multivariate IOTA coefficients of 0.88 and 0.83, indicating an almost perfect agreement (Landis and Koch, 1977). Tweets for which the two annotators did not agree on the habit label were then resolved by a third annotator. After successful validation of the consistency of the annotations, we split the remaining tweets evenly across the four annotators. In total, the labeling process yielded a dataset of 1750 (unique) annotated tweets.

The annotated tweets are then used to compare the predictions of the machine learning classifier to the human annotations, i. e., to evaluate the out-of-sample prediction performance. The machine learning classifier yields a high macro $F1$-score of 0.80 and a classification accuracy of $79.10\,\%$. Note that this can be regarded as state-of-the-art performance when it comes to fine-grained classification of tweets (Yao et al., 2020). Our machine learning classifier thus produces accurate out-of-sample predictions of whether or not individual tweets refer to certain habits.

After successful evaluation of the machine learning method, we use the model to automatically label all posts in our time series of 9.4 million tweets (i. e., predict whether each Tweet refers to one or multiple habits). These automatically labeled tweets are then used in our empirical analysis to study habit trends on Twitter during the COVID-19 pandemic.

A.3.3 List of Keywords

Here is the full list of keywords used for each habit. Various word forms of the keywords are also considered, e. g., *face masks* and *face masking* are also considered for the keyword *face mask*.

Face masks: *wear mask, face mask, mask distancing, require mask, sew mask, fabric mask, mask wearer, cloth mask, mask protect, mask gloth, facemask, require mask*

Hand washing: *hand washing, hand wash, hand sanitizer, wash hand, washing hands*

Teleworking & online studying: *remote learning, home schooling, zoom class, online learning, zoom meeting, zoom conference, zoom lecture, webex, video conference, wfh, distance learning, telework, home office, conference call, work home*

Online video conferencing: *online learning, zoom, video conference, online class, microsoft teams, skype, hangout, facetime*

Digital gaming: *esports, video game, videogame, gamertag, gamestop, nintendo, playstation, xbox, nintendo switch, wii, game console, play gta, play fifa, blizzard, valve, pokemon, skyrim, super mario, mario kart, pubg, tetris, minecraft, csgo, fortnite, psn, mmorpg, steam, gog, valorant, overwatch, gaming, gamer, animal crossing, sims, zelda, zelda botw, botw, gamer girl, rocket league, cod*

Online streaming: *itunes, apple tv, netflix, hulu, hbo, youtube, podcast, prime video, streaming*

B Appendix for Study II

B.1 Additional Results

B.1.1 Online Dating

Table B.1: Change in time spent on online dating per day during lockdowns vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.014***		0.018***	
	(0.002,0)		(0.001,9)	
Lockdown length:				
1-5 weeks		0.11***		0.079***
		(0.033)		(0.030)
6-10 weeks		0.12***		0.11***
		(0.032)		(0.029)
11-15 weeks		0.095***		0.097***
		(0.033)		(0.031)
16-20 weeks		0.21***		0.24***
		(0.037)		(0.034)
More than 20 weeks		0.14***		0.20***
		(0.037)		(0.035)
unknown		0.051		0.040
		(0.037)		(0.036)
Age			−0.0040***	−0.0037***
			(0.000,55)	(0.000,55)
Female			−0.000,28	0.0063
			(0.012)	(0.012)
Married			0.068***	0.073***
			(0.014)	(0.014)
College-level edu or higher			0.058***	0.057***
			(0.013)	(0.013)
Employed			−0.062***	−0.068***
			(0.014)	(0.014)
Self-employed			−0.042**	−0.057***
			(0.021)	(0.021)
Student			−0.062**	−0.054**
			(0.027)	(0.027)
Household size			−0.0025	−0.000,058
			(0.005,5)	(0.005,5)
Risk attitude in general			−0.0057	0.000,036
			(0.007,7)	(0.007,7)
Risk attitude in health issues			0.028***	0.019**
			(0.007,6)	(0.007,6)
Financial stress during lockdown			0.060***	0.063***
			(0.006,3)	(0.006,3)
Health status			0.038***	0.040***
			(0.006,4)	(0.006,4)
Live with kids age 0-6			0.027	0.030*
			(0.017)	(0.017)
Live with kids age 7-18			0.042***	0.039***
			(0.015)	(0.015)
Live with elderly above 65			0.044**	0.041**
			(0.019)	(0.019)
Constant	0.11*	0.076**	0.20***	0.17***
	(0.057)	(0.039)	(0.033)	(0.041)
R-squared	0.0102	0.0079	0.0314	0.0311
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent on online dating per day during lockdowns compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *p < 0.1; **p < 0.05, ***p < 0.01. Standard errors in parenthesis.

Table B.2: Change in time spent on online dating per day in expectation after Corona vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.0019		0.0035***	
	(0.001,5)		(0.001,4)	
Lockdown length:				
1-5 weeks		0.045*		0.023
		(0.023)		(0.022)
6-10 weeks		0.042*		0.026
		(0.023)		(0.021)
11-15 weeks		0.042*		0.029
		(0.024)		(0.022)
16-20 weeks		0.14***		0.13***
		(0.026)		(0.024)
More than 20 weeks		0.092***		0.090***
		(0.026)		(0.025)
unknown		0.000,24		−0.0096
		(0.026)		(0.026)
Age			−0.0017***	−0.0016***
			(0.000,40)	(0.000,40)
Female			−0.0030	−0.0020
			(0.008,9)	(0.008,9)
Married			0.039***	0.039***
			(0.010)	(0.010)
College-level edu or higher			0.015	0.012
			(0.009,5)	(0.009,5)
Employed			−0.027***	−0.028***
			(0.010)	(0.010)
Self-employed			0.018	0.011
			(0.015)	(0.015)
Student			−0.012	−0.0062
			(0.019)	(0.019)
Household size			−0.0043	−0.0041
			(0.004,0)	(0.004,0)
Risk attitude in general			−0.012**	−0.010*
			(0.005,6)	(0.005,5)
Risk attitude in health issues			0.026***	0.022***
			(0.005,5)	(0.005,5)
Financial stress during lockdown			0.016***	0.015***
			(0.004,6)	(0.004,6)
Health status			0.0060	0.0050
			(0.004,7)	(0.004,7)
Live with kids age 0-6			0.020	0.020
			(0.012)	(0.012)
Live with kids age 7-18			0.020*	0.018*
			(0.011)	(0.011)
Live with elderly above 65			0.0053	0.0029
			(0.014)	(0.014)
Constant	0.076***	0.038*	0.12***	0.099***
	(0.026)	(0.022)	(0.024)	(0.030)
R-squared	0.0009	0.0053	0.0074	0.0110
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent on online dating per day in expectation after Corona compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *p < 0.1; **p < 0.05, ***p < 0.01. Standard errors in parenthesis.

B.1.2 Online Sports

Table B.3: Change in time spent on online sports per day during lockdowns vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.017***		0.026***	
	(0.002,2)		(0.002,0)	
Lockdown length:				
1-5 weeks		0.056		0.10***
		(0.036)		(0.032)
6-10 weeks		0.060*		0.13***
		(0.035)		(0.031)
11-15 weeks		0.061*		0.14***
		(0.036)		(0.033)
16-20 weeks		0.15***		0.26***
		(0.040)		(0.036)
More than 20 weeks		0.080**		0.21***
		(0.041)		(0.037)
unknown		−0.0079		0.025
		(0.040)		(0.039)
Age			−0.0052***	−0.0049***
			(0.000,59)	(0.000,59)
Female			0.095***	0.10***
			(0.013)	(0.013)
Married			0.049***	0.056***
			(0.015)	(0.015)
College-level edu or higher			0.095***	0.095***
			(0.014)	(0.014)
Employed			−0.047***	−0.056***
			(0.015)	(0.015)
Self-employed			−0.0083	−0.024
			(0.023)	(0.023)
Student			−0.026	−0.019
			(0.029)	(0.029)
Household size			−0.000,51	0.0034
			(0.005,9)	(0.005,9)
Risk attitude in general			−0.023***	−0.015*
			(0.008,2)	(0.008,3)
Risk attitude in health issues			0.029***	0.019**
			(0.008,1)	(0.008,2)
Financial stress during lockdown			0.065***	0.070***
			(0.006,8)	(0.006,8)
Health status			0.054***	0.058***
			(0.006,9)	(0.006,9)
Live with kids age 0-6			0.040**	0.042**
			(0.018)	(0.019)
Live with kids age 7-18			0.052***	0.047***
			(0.016)	(0.016)
Live with elderly above 65			0.051**	0.050**
			(0.021)	(0.021)
Constant	0.17***	0.20***	0.19***	0.17***
	(0.057)	(0.056)	(0.036)	(0.045)
R-squared	0.0159	0.0083	0.0447	0.0404
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent on online sports per day during lockdowns compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *p < 0.1; **p < 0.05, ***p < 0.01. Standard errors in parenthesis.

Table B.4: Change in time spent on online sports per day in expectation after Corona vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.0056***		0.0086***	
	(0.001,6)		(0.001,5)	
Lockdown length:				
1-5 weeks		0.011		0.016
		(0.027)		(0.024)
6-10 weeks		0.0100		0.021
		(0.026)		(0.023)
11-15 weeks		0.022		0.043*
		(0.027)		(0.024)
16-20 weeks		0.062**		0.086***
		(0.030)		(0.027)
More than 20 weeks		0.052*		0.079***
		(0.030)		(0.028)
unknown		−0.057*		−0.050*
		(0.030)		(0.029)
Age			−0.0027***	−0.0026***
			(0.000,44)	(0.000,44)
Female			0.039***	0.042***
			(0.009,8)	(0.009,8)
Married			0.013	0.015
			(0.011)	(0.011)
College-level edu or higher			0.031***	0.029***
			(0.010)	(0.011)
Employed			−0.026**	−0.029***
			(0.011)	(0.011)
Self-employed			0.047***	0.040**
			(0.017)	(0.017)
Student			0.011	0.016
			(0.021)	(0.021)
Household size			−0.000,75	0.000,69
			(0.004,4)	(0.004,4)
Risk attitude in general			−0.019***	−0.017***
			(0.006,1)	(0.006,1)
Risk attitude in health issues			0.027***	0.022***
			(0.006,0)	(0.006,0)
Financial stress during lockdown			0.038***	0.039***
			(0.005,0)	(0.005,0)
Health status			0.027***	0.028***
			(0.005,1)	(0.005,1)
Live with kids age 0-6			0.024*	0.024*
			(0.014)	(0.014)
Live with kids age 7-18			0.0069	0.0041
			(0.012)	(0.012)
Live with elderly above 65			0.038**	0.036**
			(0.015)	(0.015)
Constant	0.11***	0.13***	0.15***	0.16***
	(0.036)	(0.042)	(0.026)	(0.033)
R-squared	0.0037	0.0044	0.0187	0.0192
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent on online sports per day in expectation after Corona compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *p < 0.1; **p < 0.05, ***p < 0.01. Standard errors in parenthesis.

B.1.3 Online Shopping

Table B.5: Change in time spent on online shopping per day during lockdowns vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.030***		0.031***	
	(0.002,4)		(0.002,2)	
Lockdown length:				
1-5 weeks		0.12***		0.17***
		(0.039)		(0.035)
6-10 weeks		0.13***		0.19***
		(0.038)		(0.034)
11-15 weeks		0.12***		0.19***
		(0.040)		(0.036)
16-20 weeks		0.20***		0.29***
		(0.043)		(0.039)
More than 20 weeks		0.11***		0.22***
		(0.044)		(0.040)
unknown		0.026		0.064
		(0.043)		(0.042)
Age			−0.0019***	−0.0015**
			(0.000,64)	(0.000,64)
Female			0.12***	0.14***
			(0.014)	(0.014)
Married			0.038**	0.046***
			(0.016)	(0.017)
College-level edu or higher			0.036**	0.039**
			(0.015)	(0.015)
Employed			−0.050***	−0.062***
			(0.016)	(0.017)
Self-employed			−0.018	−0.032
			(0.025)	(0.025)
Student			−0.080**	−0.075**
			(0.031)	(0.031)
Household size			0.013**	0.018***
			(0.006,4)	(0.006,4)
Risk attitude in general			−0.014	−0.0070
			(0.008,9)	(0.008,9)
Risk attitude in health issues			0.000,97	−0.0091
			(0.008,8)	(0.008,8)
Financial stress during lockdown			0.079***	0.087***
			(0.007,3)	(0.007,3)
Health status			0.025***	0.030***
			(0.007,5)	(0.007,5)
Live with kids age 0-6			0.057***	0.060***
			(0.020)	(0.020)
Live with kids age 7-18			0.052***	0.046***
			(0.017)	(0.017)
Live with elderly above 65			0.041*	0.043*
			(0.022)	(0.022)
Constant	0.21***	0.26***	0.13***	0.090*
	(0.048)	(0.048)	(0.038)	(0.048)
R-squared	0.0187	0.0065	0.0381	0.0308
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent on online shopping per day during lockdowns compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *p < 0.1; **p < 0.05, ***p < 0.01. Standard errors in parenthesis.

Table B.6: Change in time spent on online shopping per day in expectation after Corona vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.0088^{***}		0.0092^{***}	
	(0.001,8)		(0.001,6)	
Lockdown length:				
1-5 weeks		0.061^{**}		0.050^{*}
		(0.029)		(0.026)
6-10 weeks		0.047		0.041
		(0.028)		(0.025)
11-15 weeks		0.032		0.038
		(0.029)		(0.026)
16-20 weeks		0.11^{***}		0.11^{***}
		(0.032)		(0.029)
More than 20 weeks		0.10^{***}		0.11^{***}
		(0.033)		(0.030)
unknown		−0.011		−0.016
		(0.032)		(0.031)
Age			-0.0013^{***}	-0.0011^{**}
			(0.000,48)	(0.000,48)
Female			0.032^{***}	0.035^{***}
			(0.011)	(0.011)
Married			0.017	0.019
			(0.012)	(0.012)
College-level edu or higher			−0.0098	−0.0099
			(0.011)	(0.011)
Employed			-0.033^{***}	-0.037^{***}
			(0.012)	(0.012)
Self-employed			0.028	0.021
			(0.018)	(0.018)
Student			−0.015	−0.011
			(0.023)	(0.023)
Household size			0.010^{**}	0.011^{**}
			(0.004,7)	(0.004,7)
Risk attitude in general			-0.022^{***}	-0.019^{***}
			(0.006,6)	(0.006,6)
Risk attitude in health issues			0.019^{***}	0.015^{**}
			(0.006,6)	(0.006,6)
Financial stress during lockdown			0.026^{***}	0.027^{***}
			(0.005,5)	(0.005,5)
Health status			0.0098^{*}	0.011^{*}
			(0.005,6)	(0.005,6)
Live with kids age 0-6			0.050^{***}	0.051^{***}
			(0.015)	(0.015)
Live with kids age 7-18			0.0065	0.0049
			(0.013)	(0.013)
Live with elderly above 65			0.021	0.020
			(0.017)	(0.017)
Constant	0.12^{***}	0.12^{***}	0.11^{***}	0.099^{***}
	(0.034)	(0.037)	(0.029)	(0.036)
R-squared	0.0031	0.0031	0.0108	0.0112
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent on online shopping per day in expectation after Corona compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. $^{*}p < 0.1$; $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors in parenthesis.

B.1.4 Social Media

Table B.7: Change in time spent on social media per day during lockdowns vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.069***		0.089***	
	(0.005,5)		(0.004,9)	
Lockdown length:				
1-5 weeks		0.26***		0.43***
		(0.089)		(0.080)
6-10 weeks		0.28***		0.46***
		(0.088)		(0.078)
11-15 weeks		0.22**		0.42***
		(0.091)		(0.081)
16-20 weeks		0.46***		0.70***
		(0.099)		(0.090)
More than 20 weeks		0.27***		0.56***
		(0.10)		(0.092)
unknown		−0.016		0.0098
		(0.098)		(0.096)
Age			−0.010***	−0.0090***
			(0.001,5)	(0.001,5)
Female			0.25***	0.28***
			(0.033)	(0.033)
Married			0.040	0.062
			(0.038)	(0.038)
College-level edu or higher			0.041	0.049
			(0.035)	(0.035)
Employed			−0.13***	−0.17***
			(0.038)	(0.038)
Self-employed			−0.053	−0.089
			(0.056)	(0.057)
Student			0.075	0.082
			(0.071)	(0.072)
Household size			0.057***	0.071***
			(0.015)	(0.015)
Risk attitude in general			0.019	0.039*
			(0.020)	(0.020)
Risk attitude in health issues			−0.016	−0.043**
			(0.020)	(0.020)
Financial stress during lockdown			0.27***	0.30***
			(0.017)	(0.017)
Health status			0.080***	0.095***
			(0.017)	(0.017)
Live with kids age 0-6			0.081*	0.089*
			(0.046)	(0.046)
Live with kids age 7-18			0.11***	0.092**
			(0.040)	(0.040)
Live with elderly above 65			0.066	0.070
			(0.051)	(0.052)
Constant	0.71***	0.83***	0.59***	0.56***
	(0.16)	(0.21)	(0.088)	(0.11)
R-squared	0.0280	0.0092	0.0639	0.0525
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent on social media per day during lockdowns compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *p < 0.1; **p < 0.05, ***p < 0.01. Standard errors in parenthesis.

Table B.8: Change in time spent on social media per day in expectation after Corona vs before Corona (in hour)

	(1)	(2)	(3)	(4)
Number of bans	0.019^{***}		0.025^{***}	
	(0.004,0)		(0.003,6)	
Lockdown length:				
1-5 weeks		0.12^{*}		0.13^{**}
		(0.065)		(0.058)
6-10 weeks		0.13^{**}		0.15^{***}
		(0.064)		(0.057)
11-15 weeks		0.13^{*}		0.16^{***}
		(0.066)		(0.059)
16-20 weeks		0.35^{***}		0.39^{***}
		(0.072)		(0.066)
More than 20 weeks		0.25^{***}		0.30^{***}
		(0.073)		(0.067)
unknown		0.012		0.0052
		(0.072)		(0.070)
Age			-0.0039^{***}	-0.0034^{***}
			(0.001,1)	(0.001,1)
Female			0.057^{**}	0.066^{***}
			(0.024)	(0.024)
Married			0.069^{**}	0.074^{***}
			(0.028)	(0.028)
College-level edu or higher			0.042^{*}	0.039
			(0.025)	(0.026)
Employed			-0.048^{*}	-0.057^{**}
			(0.028)	(0.028)
Self-employed			0.093^{**}	0.071^{*}
			(0.041)	(0.041)
Student			0.17^{***}	0.18^{***}
			(0.052)	(0.052)
Household size			0.010	0.013
			(0.011)	(0.011)
Risk attitude in general			-0.056^{***}	-0.048^{***}
			(0.015)	(0.015)
Risk attitude in health issues			0.078^{***}	0.065^{***}
			(0.015)	(0.015)
Financial stress during lockdown			0.087^{***}	0.090^{***}
			(0.012)	(0.012)
Health status			0.026^{**}	0.027^{**}
			(0.012)	(0.012)
Live with kids age 0-6			0.042	0.044
			(0.033)	(0.033)
Live with kids age 7-18			-0.021	-0.027
			(0.029)	(0.029)
Live with elderly above 65			0.053	0.049
			(0.037)	(0.037)
Constant	0.26^{***}	0.22^{**}	0.21^{***}	0.16^{**}
	(0.070)	(0.090)	(0.064)	(0.080)
R-squared	0.0042	0.0053	0.0150	0.0160
Number of observations	17,728	17,728	17,728	17,728

This table shows the random-effect models on the change of time spent on social media per day in expectation after Corona compared to before Corona, as a function of the strictness of the lockdown (measured by the reported number of governmental interventions during lockdowns), the reported length of lockdowns, in addition to other individual characteristics. The models control for country random effects. Risk attitudes in general, risk attitudes in health issues, financial stress level during lockdowns and perceived health status are standardized variables. *p < 0.1; **p < 0.05, ***p < 0.01. Standard errors in parenthesis.

C Appendix for Study III

C.1 Experimental Instructions

Welcome

Welcome and thank you for participating in today's experiment. For your participation, you will in any case receive 1.5 GBP. You can earn additional money by performing two investment tasks. The final payment will depend on both chance and your choices. Thus, it is important for you to understand the instructions before the experiment starts. Details of the investment tasks are explained on the following screens.

Please enter your Prolific-ID before you continue:____

Instruction for Investment Task 1

You will perform the following investment task once. The money you earn in the task is calculated in tokens with an exchange rate from tokens to GBP 0.05. **That is: 100 tokens = 5.0 GBP**. We will convert your earnings to GBP after the investment task. We will round your earnings down to the closest 0.01 GBP.

You are endowed with 100 experimental tokens, and you choose how much to invest in two investment opportunities: P and T. The success or failure of these opportunities depends on the overall state of the economy. With probability ½, the economy grows fast and with probability ½, the economy grows slowly. If the economy grows fast, both opportunities succeed, and if the economy develops slowly, both opportunities fail. **That is, either both opportunities succeed or both opportunities fail**. The return per token invested in each opportunity is as follows:

Investment Opportunity P: with probability ½ (that is, in fast-growth economy state), you receive 0.9 times the amount you have invested in addition to your initial investment; and with probability ½ (that is, in slow-growth economy state), you lose 80% of the amount you have invested.

Investment Opportunity T: with probability ½ (that is, in fast-growth economy state), you receive 1.7 times the amount you have invested in addition to your initial investment; and with probability ½ (that is, in slow-growth economy state), you lose the amount you have invested.

Economy State	Fast	Slow
Probability	½	½
Opportunity T	2.7	0
Opportunity P	1.9	0.2

You can split the tokens in any way you like. That is, you can put some tokens in opportunity T, some in opportunity P, and keep some tokens uninvested. You can also only pick one opportunity to invest or keep all the tokens uninvested. The investment payouts are rounded down to the closest 0.01 GBP. (Treatment group[1]: **Before you make the decision, you will receive advice from a previous participant**. Details of the advice receiving procedure are presented on the following screen.) To sum up, if you invest **t** in opportunity **T** and **p** in opportunity **P** your earnings are:

$$Earning = \begin{cases} 100 + 1.7t + 0.9p & \text{in fast-growth state} \\ 100 - t - 0.8p & \text{in slow-growth state} \end{cases}$$

Instruction for Investment Task 1

Control Questions

Before we continue we would like to verify your understanding of the investment task.

Question 1: Suppose you have invested 40 tokens in opportunity T, 40 tokens in opportunity P, and left 20 tokens uninvested, is it possible that you earn money on your investment in opportunity T and lose money on your investment in opportunity P? Yes/No

[1] The contents in blue are additional instructions for the treatment group.

Question 2: Suppose you have invested 40 tokens in opportunity T, how much can you invest in opportunity P?

Only exactly 60 tokens./ Any number of tokens from 0 to 60./ Any number of tokens.

Investment Task 1 - Advice

Only relevant for the treatment group:

Before taking the decision, you have a chance to see advice given to you by a previous participant. The advisors practiced the same investment task for 2 minutes, and are rewarded for providing you with high quality advice. They will provide you with their suggestions on how much money to invest in each opportunity, and an explanation of their reasoning. You do not have to follow the advice given. You are able to choose one advisor from a list of 7 advisors. You will be informed about:

- their simulated earning from the last round investment task that they practiced
- how tolerant they reported that they are for taking risks
- their gender
- whether they are interested in finance and investing
- their reported education level

Advice Selection

Only relevant for the treatment group:

Now you can choose your advisor. You can choose between the following advisors.

Advice

Only relevant for the treatment group:

You have chosen Advisor 3. Here is his data:

	Avg. earnings	Risk tolerance	Gender	Interest in finance	Education level
Advisor 3	117.5	High	Male	Yes	Technical/community college

	Simulated earnings	Risk tolerance	Gender	Interest in finance/ investing	Reported education level
Advisor 1	128	Medium	Male	Yes	bachelor's degree
Advisor 2	117.5	High	Male	Yes	high school diploma / A-levels
Advisor 3	117.5	High	Male	Yes	Technical/community college
Advisor 4	135	Low	Female	Yes	bachelor's degree
Advisor 5	124.5	Medium	Male	Yes	bachelor's degree
Advisor 6	113.25	Low	Male	No	PhD
Advisor 7	128	Medium	Female	Yes	bachelor's degree

Advisor 3 offers you the following advice:

You should invest 0 in opportunity P. You should invest 50 in opportunity T.

The advisor provided the following explanation:

On average, T is better than P. Average outcome T: 2.7*0.5 = 1.35 Average outcome P: 1.9*0.5 + 0.2*0.5 = 1.05. To reduce variance and risk of immediately losing 100% of your investment, it is advised to invest 50/100 tokens for an expected return of 67.5 tokens. If multiple rounds were permitted, this would then allow subsequent investments to scale based on a previous positive or negative outcome.

You will still see the advice when you make your investment decision.

Investment

You can make your investment decision now. Please, remember that:

- you can invest any amount from the 100 tokens you wish
- you can invest in both opportunities
- both investment opportunities earn money
- if the economy grows fast, and both lose money if it grows slow
- the summary of the investment returns per token invested is given by the table below

Economy State	Fast	Slow
Probability	½	½
Opportunity T	2.7	0
Opportunity P	1.9	0.2

only relevant for the treatment group:

You have received the following advice:

You should invest 0 in opportunity P.

You should invest 50 in opportunity T.

The advisor provided the following explanation:

On average, T is better than P. Average outcome T: 2.7*0.5 = 1.35 Average outcome P: 1.9*0.5 + 0.2*0.5 = 1.05. To reduce variance and risk of immediately losing 100% of your investment, it is advised to invest 50/100 tokens for an expected return of 67.5 tokens. If multiple rounds were permitted, this would then allow subsequent investments to scale based on a previous positive or negative outcome.

How many tokens would you like to invest in opportunity P? _

How many tokens would you like to invest in opportunity T? _

You have _ tokens left.

You have at least 60 seconds to make the decision.

Explanation

Please, explain the reasoning behind your decision: ____

Helpfulness Rating

only relevant for the treatment group:

Please, rate the usefulness of the advice.

Not usefull at all 1 2 3 4 5 Very useful

Investment Task 2

Investment task 2 is an opportunity to sell your first investment.

You can sell your investment portfolio, which includes both your investment and the amount you left uninvested. Computer has randomly generated a price from 0 to 275 tokens. It will offer to buy your portfolio at this price. **Please determine the lowest acceptable price for your portfolio**.

If the randomly generated price is above the lowest acceptable price, the transaction will be made. **You will receive the randomly generated price, but not the lowest acceptable price you stated**. Otherwise, you will keep the investment. The randomly generated price is completely unrelated to your stated price. Your best strategy is to determine the minimum amount you would be willing to sell your portfolio for and report it.

Example: if you reported that the lowest acceptable price for your portfolio is 20 tokens and the randomly generated price is 30 tokens, the transaction will be made. You receive 30 tokens and forgo your potential earnings in Opportunity T and P and also the amount that has been left uninvested.

You have invested t tokens in Opportunity T, P tokens in Opportunity P and left (100-t-p) tokens uninvested. **This means**:

- With probability ½ (in fast growing economy), you receive $(100 + 1.7t + 0.9p)$ tokens
- With probability ½ (in slow growing economy), you receive $(100 - t - 0.8p)$ tokens

Now, please think carefully and determine the minimum number of tokens that you would like to sell your investment portfolio, which includes your investment in P and T and also the uninvested amount. **The lowest acceptable price for my portfolio is**: ____

You have at least 90 seconds to make the decision.

Feedback

The randomly generated price is 181 tokens. Your lowest acceptable price is 3 tokens.

Your offer is less than the randomly generated fixed offer. You sell your investment and receive xxx tokens. This converts to xxx GBP. Your total earning from the experiment is xxx GBP. After you complete a short survey, we will transfer the payment to your prolific account.

Survey

How do you see yourself?

Risk taking in general: are you generally a person who is fully prepared to take risks or do you try to avoid risks? Please use the following slider to rate yourself, where the value 0 means "not at all willing to take risks" and value 10 means "very willing to take risks".

0: not at all willing to take risks 10: very willing to take risks

Risk taking in financial issues: are you generally a person who is fully prepared to take risks or do you try to avoid risks **in financial issues**? Please use the following slider to rate yourself, where the value 0 means "not at all willing to take risks" and value 10 means "very willing to take risks".

0: not at all willing to take risks 10: very willing to take risks

Please use the slider to choose a rating for each question to proceed with the experiment.

Survey

To finish the experiment, please, complete the following survey What is your gender?

- Male
- Female
- Other
- Prefer not to declare

Are you interested in finance and/or investing?

- Yes
- No

Did you take courses on economics/finance?

- Yes
- No

What is your highest education?

- less than high school diploma
- high school diploma / A-levels
- Technical/community college
- bachelor's degree
- master's degree
- PhD
- other

C.2 Additional Results

C.2.1 Investment Choice

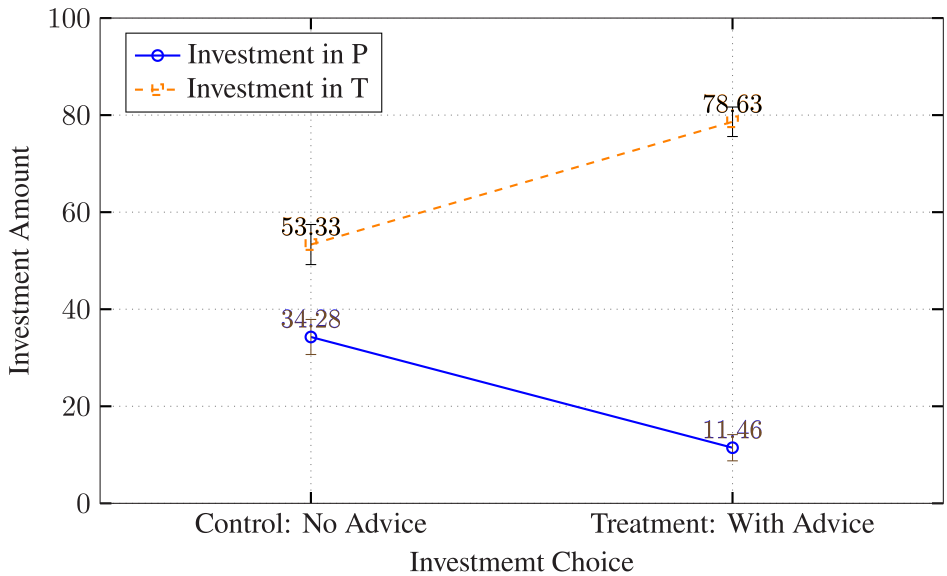


Figure B1: Interaction plot on investment choice. Error bars represent 95% confidence intervals.

C.2.2 Advice from Advisor

Table B1: Advisor information

Advisor	Advice P	Advice T	Simulated Earn.	Gender	Reported Edu.	Risk Tolerance	Interest in Finance
1	0	100	135	Female	Bachelor	Low	Yes
2	0	80	128	Female	Bachelor	Medium	Yes
3	0	80	128	Male	Bachelor	Medium	Yes
4	35	65	124.5	Male	Bachelor	Medium	Yes
5	0	50	117.5	Male	High School/A-level	High	Yes
6	0	50	117.5	Male	Community College	High	Yes
7	34	33	113.25	Male	PhD	Low	No

Table B2: Detailed Advice from advisors

Advisor	Advice in P	Advice in T	Advice Explanation
1	0	100	The odds are the same wherever you invest but the opportunity to earn more is better with Opportunity T. I would advise that you go all in on this opportunity for this reason.
2	0	80	Assuming a slow growing economy, investing all 100 tokens in P will leave you with 20. Investing only 80 into T carries the same risk as it will also leave you with the uninvested 20. Assuming a fast growing economy, investing 100 tokens in P will only gain you 190. Investing 80 tokens into T will gain 216. Therefore there's no point investing in P. The amount of tokens put into T could be higher than 80 if you want to take a risk or lower than 80 if you're more risk averse.
3	0	80	By holding back 20 tokens, we ensure that even if there is slow growth, we end up with at least 20 tokens. If growth is fast, we get a 2.7x return on our 80 invested tokens - gaining 216 tokens. Plus the 20 tokens we held back, for a total return of 236 tokens, or 2.36x. This is better than the 1.9x return of Opportunity P. So, in either the lucky (fast growth) or unlucky (slow growth) scenario, we achieve return that is the same or better than Opportunity P, with no additional risk.
4	35	65	I follow a more risk-averse investment style therefore I prefer to cover all eventualities when making investment decisions. This means for this decision, I want a weighted bias towards a fast growth scenario but an 'insurance' investment were a slow growth scenario occur. I want to be able to maximise my potential investment return whilst ensuring a return in slower growth. I reasoned that there were only 2 scenarios where you are guaranteed 0 return and this was as follows: 1. 100% opportunity T and slow growth; 2. Don't invest all tokens As such, it is necessary to: 1. Split across both opportunity T and P with a heavier weighting to opportunity T, and; 2. Use all tokens available to maximise potential return A 50/50 split would provide better yields for a slow growth scenario but would hinder your returns in a fast growth environment (1/2 chance).
5	0	50	Investment T has higher risk and higher returns than P. The slow growth scenario for investment P is better than T, but is not worth the risk, given that you can also not invest in either. Therefore I would recommend investing an amount you are comfortable losing into T, and leave the remainder uninvested.
6	0	50	On average, T is better than P. Average outcome T: 2.7*0.5 = 1.35 Average outcome P: 1.9*0.5 + 0.2*0.5 = 1.05. To reduce variance and risk of immediately losing 100% of your investment, it is advised to invest 50/100 tokens for an expected return of 67.5 tokens. If multiple rounds were permitted, this would then allow subsequent investments to scale based on a previous positive or negative outcome.
7	34	33	Not investing will leave you an average return of 100. By splitting evenly, your average outcome will be better than 100.

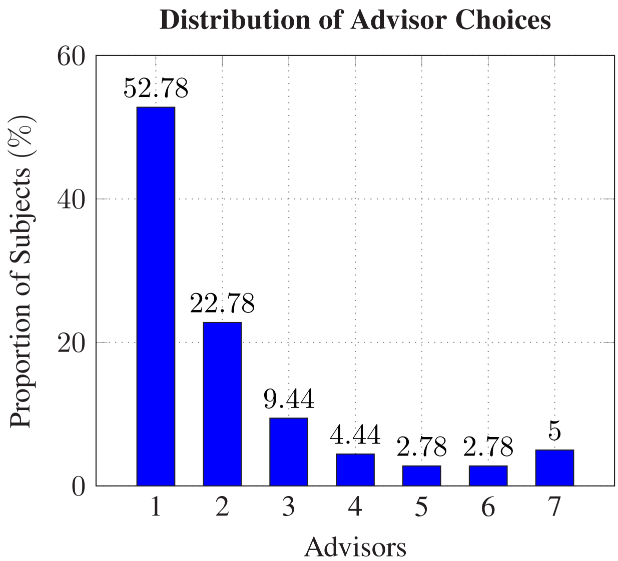


Figure B2: The figure shows the distribution of advisor choice among subjects in the treatment group.

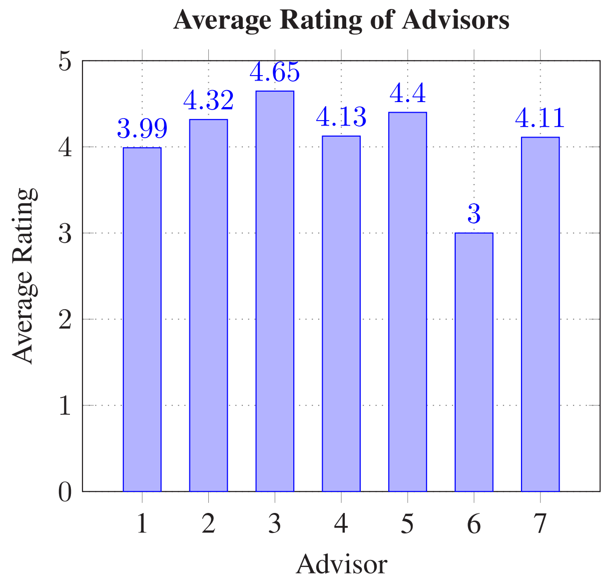


Figure B3: Average rating of advisors' advice, where 1 indicates "not helpful at all" and 5 indicates "very helpful".

Table B3: This table shows the number of subjects in the treatment and control whose choices were identical to the investment strategies from advice.

Investment Strategy (P,T)	Treatment	Control
(0, 100)	52	23
(0, 80)	29	2
(35, 65)	6	0
(0, 50)	0	2
(34, 33)	9	0

To address the concern that portfolios picked by advisors are generally commonly chosen, we treat the portfolios as points $(t, p) \in \mathbb{R}^2$ and take the Euclidean distance between portfolios as a measure of their difference. We calculate the distance between each treated subject's chosen portfolio and the portfolio recommended by their selected advisor, and compare this to two benchmarks. The first benchmark is the average distance between portfolios of untreated subjects and all advised portfolios. The second benchmark uses the minimum distance between each untreated subject's portfolio and the closest advised portfolio. As shown in Table B4, in both cases, the average distance is significantly smaller for treated subjects than for those in the control group—a difference that is statistically significant at the 1% level. Moreover, within the treatment group, every subject selected the advisor whose recommended portfolio was closest to their own choice.

Table B4: Average distance between advised portfolio and the chosen portfolio

Treatment ($n = 180$)	Control: average distance ($n = 178$)	Control: minimal distance ($n = 178$)
15.08	47.76***	23.19***

Notes: This table shows the average distance between advised portfolio and the chosen portfolio for the treated subjects, as well as the averages for average and minimum distance between the chosen portfolio and portfolios of the advisors for the untreated subjects. *** denote significant differences from treatment group at 1% level, based on two-sided t-test.

C.2.3 Effect of Demographic Factors

C.2.3.1 Investment choice

As presented in Table B5, subjects in the treatment group allocated significantly less to the dominated option compared to the control group ($\beta = 23.14, p < 0.001$), while investing significantly more in the undominated option ($\beta = 25.54, p < 0.001$). These effects are robust to controls for demographic and behavioral factors, including age, gender, educational attainment (bachelor's degree), risk preferences, interest or prior education in finance. These results provide robust support for Hypothesis 1a, 1b, and 1c, suggesting that advice increases investment quality.

As presented in Table B5, demographic factors exhibit varied effects on investment decisions. Older participants allocated slightly more to the dominated option P ($\beta = 0.192, p < 0.05$), suggesting a potential age-related propensity for suboptimal investment choices. Female participants, on average, invested 5.16 tokens less in the riskier option compared to males, and this difference is marginally significant ($p < 0.1$).

Table B5: Linear regressions of investment choice on treatment and other demographic factors

	Investment in dominated asset (P)	Investment in undominated asset (T)	Total investment
Treatment	-23.14***	25.54***	2.41
	(2.26)	(2.56)	(1.95)
Age	0.19**	-0.10	0.10
	(0.10)	(0.11)	(0.08)
Female	3.31	-5.16*	-1.85
	(2.37)	(2.68)	(2.04)
Bachelor	-3.54	3.45	-0.09
	(2.51)	(2.84)	(2.16)
Risk tolerance	-0.45	1.68***	1.23***
	(0.46)	(0.53)	(0.40)
Interest in finance	6.23**	-5.98*	0.26
	(2.69)	(3.04)	(2.32)
Courses in finance	4.70	-2.05	2.65
	(2.97)	(3.36)	(2.56)
Constant	24.79***	52.84***	77.63***
	(6.11)	(6.91)	(5.27)
R-squared	0.25	0.25	0.04
Observations	358	358	358

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Interestingly, interest in finance and prior courses in finance did not appear to enhance the quality of investment decisions. On the contrary, participants who reported interest in finance invested 6.23 tokens more in the dominated option P ($p < 0.05$) and 5.98 tokens less in the undominated option T ($p < 0.1$), suggesting that a self-reported interest in finance may not necessarily translate into better decision-making outcomes. Similarly, individuals who indicated having taken finance courses invested slightly more in the dominated option P ($\beta = 4.699$) and less in the undominated option T ($\beta = 2.053$). However, the coefficients for these variables were not statistically significant. Additionally, self-reported risk tolerance was positively associated with investment in the riskier undominated option T and with total investment levels. A single unit increase on 11 unit scale is associated with 1.68 tokens larger investment in the undominated asset T ($p < 0.01$), and 1.23 tokens larger total investment ($p < 0.01$).

C.2.3.2 Earnings

Consistently with direct comparison of two experimental groups, the regressions demonstrate that being exposed to a choice of advisor results in an over 20 ($p < 0.01$) tokens payoff increase in the good state, at a cost of 7 ($p < 0.01$) tokens payoff decrease in the bad state. Female subjects earn on average 1.6 tokens less than male subject ($p < 0.1$) , and the difference is driven mostly by lower earnings in the high-state. Interest in finance has a slightly higher negative impact on expected earning ($\beta = -1.78$, $p < 0.1$). As expected, the most important demographic determinant of portfolio performance is risk attitude. A unit increase on a 11 unit scale of self-declared risk tolerance increases good-state earnings by 2.43 tokens ($p < 0.01$), at a cost of decrease in bad-state earning by 1.32 tokens ($p < 0.1$)

Table B6: Linear regression results on earnings in different states

	Bad-state Earning	Good-state Earning	Expected Earning
Treatment	-7.03***	22.60***	7.78***
	(1.88)	(3.32)	(0.82)
Age	-0.06	0.01	-0.02
	(0.08)	(0.14)	(0.03)
Female	2.51	-5.79*	-1.64*
	(1.96)	(3.47)	(0.86)
Bachelor	-0.62	2.68	1.03
	(2.08)	(3.68)	(0.91)
Risk Tolerance	-1.32***	2.45***	0.56***
	(0.39)	(0.68)	(0.17)
Interest in Finance	0.99	-4.55	-1.78*
	(2.23)	(3.95)	(0.98)
Courses in Finance	-1.71	0.74	-0.48
	(2.47)	(4.36)	(1.08)
Constant	27.32***	212.10***	119.70***
	(5.08)	(8.97)	(2.22)
R-squared	0.08	0.16	0.24
Observations	358	358	358

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.2.4 Welfare

	Rationalisable CE	**Below 100**	**Above good-state earning**
Control	116 (65.17%)	47 (26.4%)	15 (8.43%)
Treatment	116 (64.44%)	52 (28.89%)	12 (6.67%)

Table B7: The table shows the number and proportion of people who reported rational CE and irrational CE

We additionally verify how the welfare is affected by the demographic factors. Aside from the treatment effect, risk aversion is the only variable that significantly predicts certainty equivalents, with more risk-tolerant individuals reporting higher valuations—consistent with standard economic theory.

Table B8: Linear regression of certainty equivalents elicited using BDM mechanisms.

	Whole Sample (1)	Rationalisable Sample (2)
Treatment	4.80	13.94**
	(7.89)	(6.14)
Age	-0.11	-0.36
	(0.34)	(0.27)
Female	-9.00	-9.11
	(8.26)	(6.31)
Bachelor	1.19	-6.07
	(8.76)	(6.90)
Risk attitude	2.79*	2.01
	(1.62)	(1.30)
Interest in finance	9.08	-0.86
	(9.39)	(7.35)
Courses in finance	9.29	8.64
	(10.37)	(8.13)
Constant	119.90***	170.60***
	(21.34)	(17.44)
R-squared	0.03	0.07
Observations	358	232

Notes: Linear regression of certainty equivalents elicited using BDM mechanisms. Panel on the left depicts the entire sample, and panel on the right depicts only those subjects whose choices could be rationalized by an expected utility theory. Column (1) reports estimates for the full sample; Column (2) shows results for the rationalisable subsample. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To allow for a possibility that subjects whose preferences cannot be rationalize by expected utility theory, are especially harmed by receiving advice, and overall possibility of choosing an advisor harms subject welfare we conduct a series of simulation exercises. In our exercises, we analyze all possible pairs consisting of one subject from a control group and one subject from a treatment group. For each pair, we try to understand the consequences of swapping the chosen portfolios between subjects, following three measures. We verify if there is a First-Order Stochastic Dominance Relationship between the two portfolios, so that one subject in the pair would be always better-off choosing the investment of the other.[2] For more detailed analysis, we impose additional assumptions on subjects' preferences and behavior. Specifically, we assume that (i) subjects are risk-averse and (ii) have a standard CRRA utility function. Additionally, we assume that (iii) while subjects might have chosen suboptimal portfolio, they at the very least prefer their chosen portfolio to a safe option of keeping all the endowment uninvested. Under the three aforementioned assumptions, we are able to estimate the upper-bound of subjects' risk-aversion coefficients. Then, for each subject in each pair, we are able to verify if for some feasible coefficient of risk-aversion, subject is better-off keeping their portfolio rather than replacing it with the portfolio of their partner. Finally, we repeat the exercise for CARA utility function.

Table B9 summarizes the results of the exercises. The left column of Table B9 displays the probability that a random subject in a given experimental condition would be better-off if their chosen portfolio were replaced with a random portfolio from a different experimental condition. In essence, it stipulates that if subjects were to switch the experimental condition, they would behave entirely at random. Hence, it can be seen as the lower bound on the share of subjects who would benefit from switching the experimental condition, as the subjects tend to choose the portfolios to fit their own preferences. The right column of Table B9 displays the probability that a random subject in a given experimental condition would be better-off choosing at least one portfolio from a different experimental condition. In essence, it stipulates that if subjects were to switch an experimental condition, they would behave as the best-behaving subject for

[2] In our simple setup, First and Second Order Stochastic Dominance relations are equivalent.

their preferences. In that sense, the right column can be seen as the upper bound on the share of subjects who would benefit from switching the condition.

	random subject	**at least one subject**
FOSD		
control	7.38 %	64.04 %
treatment	0.28 %	12.22 %
CRRA		
control	39.65 %	80.90 %
treatment	5.88 %	25.00 %
CARA		
control	53.94 %	81.46 %
treatment	8.97 %	37.78 %

Table B9: Probability that a random subject in a given experimental condition is better off when their portfolio is replaced by a portfolio of random/at least one subject from different experimental condition.

Table B9 shows that, regardless of the chosen measure, the share of subjects who benefit from switching the experimental condition from control to treatment is a magnitude higher than the share of subjects who benefit from switching from treatment to control. This suggests that while some subjects might have been harmed by being exposed to advice, most cases receiving advice results in higher welfare.

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