Time Out for Trading*

Fatima Zahra Filali Adib† Steffen Andersen‡ Kasper Meisner Nielsen§

Akash Raja¶

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Abstract

We examine how time frictions affect stock market participation and portfolio rebalancing. We exploit plausible exogenous variation in time constraints arising from mandated self-isolation of close contacts during the COVID-19 pandemic. Trading propensity increases by 20% during quarantine, with stronger impacts for young and child-free individuals, who experience a sharp relaxation of time constraints due to fewer household responsibilities. In the longer term, close contacts are 3.5% more likely to participate in the stock market. However, the increase in active trading decisions is associated with lower returns. Overall, we provide causal evidence that time frictions shape individual portfolio choices.

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†Copenhagen Business School. Email: fzfa.fi@cbs.dk.

‡Danmarks Nationalbank. Email: sta@nationalbanken.dk.

§Copenhagen Business School. Email: kmn.fi@cbs.dk.

¶Copenhagen Business School. Email: akra.fi@cbs.dk.

Many individuals choose not to participate in the stock market, and if they do, they are slow to rebalance their portfolios. A popular explanation for these phenomena is participation costs in the form of monetary costs or time constraints (Vissing-Jorgensen (2002), Gomes and Michaelides (2005)). Despite the importance of participation costs in explaining individual portfolio choice, the empirical evidence on their nature and impact is scant. In this study, we exploit plausible exogenous variation in time constraints arising from mandated self-isolation of close contacts during the COVID-19 pandemic to quantify the impact of time frictions on trading behavior.

Studying the impact of time constraints is challenging for two reasons: first, life events that affect available time such as childbirth or changes in employment status are hardly random, raising concerns about selection bias. Second, even if random variation—such as mass layoffs—can be identified, drawing conclusions from these events about the impact of time is confounded by economic conditions. For example, job loss will relax time constraints during the unemployment spell, but is also associated with lower income and higher risk, which both directly affect portfolio decisions. Similarly, becoming a parent will both tighten time and budget constraints.

We overcome these two challenges by exploiting plausible exogenous variation in time constraints arising from the quarantining of close contacts during the COVID-19 pandemic in Denmark. Our institutional setting is helpful for two reasons: first, the Danish National Board of Health introduced a strategy involving a mass testing scheme, tracing of close contacts, and home isolation of infected individuals and close contacts. Close contacts of COVID-infected individuals were required to quarantine for one week and get tested twice (on days 4 and 6) to minimize the potential spread of the virus. This allows us to exploit the quarantines of close contacts as a plausible source of exogenous variation in individuals' available time. Second, we exploit detailed administrative register data to address concerns about the confounding effect of economic conditions on portfolio choice. We do this by forming a control group of individuals with similar characteristics to the close contacts.

Our key identifying assumption is that the timing of a close contact's quarantine is random relative to the timing of the investment decision. This effectively allows us to isolate the impact of a relaxation of time constraints on portfolio choice.

Our study starts by documenting sharp increases in stock market participation and trading activity observed during the pandemic.[1] To understand whether variations in time constraints could be driving heightened activity in the stock market, we examine whether participation increased more for individuals for whom the COVID-induced relaxation in time constraints would be more significant. In line with this hypothesis, we observe the strongest increases in participation for younger individuals and those put on furlough by their employers. We further show that the impact is weakest for individuals with a child of nursery or primary school age (age 2-9). This likely reflects time required caring for younger children and ensuring they complete their schoolwork from home. All together, these descriptive patterns indicate that available time can play a role in determining investment decisions.

As highlighted above, the concern with interpreting these marginal effects as evidence of a relaxation of time constraints is that being younger or having young children can be correlated with other traits that in turn might affect trading activity. This therefore lends itself to our main identification strategy: close contacts of COVID-infected individuals. We obtain individual-level COVID test data for the entire Danish population to identify people who test positive for the virus. Using address information linked to each individual, close contacts are then defined as people who live with the infected person. We focus on close contacts who did not test positive themselves, as a COVID infection itself could affect trading propensities through the adverse health effects. We also focus on the period from May to December 2020 for two reasons: first, this period is after the economy had reopened following the first national lockdown but before the second lockdown. Focusing on this period gives meaningful variation in available time. In particular, spending an additional hour on stock market trading has a much lower opportunity cost during quarantine because you cannot

[1] This rise in trading by retail investors on both the extensive and intensive margins echoes what has been observed in other countries (e.g., Ozik et al. (2021), Greenwood et al. (2023)).

meet friends or participate in social activities regardless. Second, the vaccination program started in late December 2020 and quarantine rules for close contacts became dependent on vaccination status. Looking at the period before vaccinations were introduced therefore helps with identification, as the decision to be vaccinated is not random.

The set of close contacts becomes our treatment group for the analysis. We then form a control group for comparison. Our control group is drawn from the set of untreated households. We exactly match treated individuals on various demographic characteristics such as age, gender, number of children, whether the family has a child of nursery or primary school age, stock market participation status, and municipality, and select the three closest matches based on financial wealth. Having obtained a treatment and control group, we adopt a staggered difference-in-differences with individual and time fixed effects. The inclusion of individual fixed effects ensures that we use within-individual variation in trading propensity, while controlling for aggregate trends is achieved through the inclusion of time fixed effects and the comparison to a matched control group.

Our baseline specification finds a strong positive effect of a loosening of time constraints on trading propensity. Close contacts exhibit similar trading propensities to the control group in the weeks leading up to the infection. During the infection week, the probability of making a trade increases by 20% for the close contacts relative to the control group. Thereafter, the impact on trading propensity remains large and positive, indicating persistent effects of a temporary relaxation of time frictions. These baseline results demonstrate that time frictions can play a role determining trading intensity.

We then study whether there is heterogeneity in the impact of time by individual characteristics. In line with the findings in our descriptive analysis, the effect is driven by young individuals (age 20-29) and those without children. The marginal effect of time is positive and significant for child-free individuals but is insignificant for those with young children, perhaps reflecting the impact of caring responsibilities associated with having a potentially unwell child who has to stay home from school. The stronger effects for younger and child-free individuals again suggest that time matters for the propensity to trade.

We also split the sample between those who were participating prior to the date of self-isolation, and those who were not. We find similar economic magnitudes for the effects for the two subgroups ($\approx$ 20% increase in the probability of making a trade), suggesting that time frictions play a role at the extensive margin (entry decisions), as well as the intensive margin (trading intensity). These patterns indicate that limited time is a factor in explaining why some people may not enter the stock market (entry costs to participation) and also why people may be inertial in their portfolio rebalancing (per-period participation costs).

Having established an increase in trading propensity during the quarantine week, we examine the nature of such trades. Our goal is to further understand if the rise in trading activity is aligned with recreational trading. We first split stock and mutual fund trades. Both asset classes show a significant increase in trading, though the relative increase is greater for funds ($\approx$ 40%) than stocks ($\approx$ 15%). We also investigate the types of trades made by the control and treatment groups by analyzing the proportion of trades in funds and stocks. Within stocks, we further distinguish between stocks belonging to the main Danish index (OMX Copenhagen 25), non-OMX Danish stocks, and foreign stocks. We find that, conditional on making a trade, the treatment and control groups trade in a very similar way before and after the quarantine. As such, the relaxation of time constraints leads to more trading, though not necessarily of different types of assets compared to the control group. Together, these findings suggest that recreational trading is not driving all of our results.

A natural question to now ask is whether the effects are temporary: a short-term relaxation of time constraints leads to more trading today, but then once time constraints revert to normal, do people continue to participate? We investigate the likelihood of participating in the stock market over the next 12 months. Participation rates of close contacts increased by 3.5% relative to their matched control group one year after the infection, suggesting that even a temporary loosening of time constraints that induces entry can have long-lasting effects on stock market participation. On the returns side, we find that close contacts have lower cumulative returns of about 2 percentage points 12 months after the infection compared to the control group. The lower returns are driven purely by active stock selection. Instead, we find no difference in returns for the part of the portfolio that is allocated to mutual funds. This suggests that while more time can lead to more participation over a longer horizon, this does not necessarily translate into better performance, particularly for investors who pick individual stocks.

Our contribution to the literature is threefold: first, we relate to the broad literature on limited stock market participation (Mankiw and Zeldes (1991), Haliassos and Bertaut (1995), Guiso et al. (2003)). A popular explanation for why, in contrast to predictions from standard portfolio choice theory (Samuelson (1969), Merton (1969, 1971)), many people choose not to invest in the stock market is participation costs (Vissing-Jorgensen (2002), Gomes and Michaelides (2005), Alan (2006)).[2] Participation costs are a commonly-used ingredient in life-cycle models of participation choice to generate nonparticipation (e.g., Gomes and Michaelides (2005), Fagereng et al. (2017), Choukhmane and de Silva (2024)). In line with a participation cost story, empirical studies find a strong correlation between participation rates and wealth (Guiso et al. (2003), Vissing-Jorgensen (2002), Campbell (2006)), and have documented entry into the stock market after receiving windfall wealth from inheritances or lotteries (Andersen and Nielsen (2011), Briggs et al. (2021)). Two recent studies provide evidence related to the nature of participation costs: Even-Tov et al. (2022) find that monetary fees are negatively associated with trading activity, and Hvide et al. (2024) show that stock market participation and trading activity increase when investors get access to broadband internet. In comparison to these studies, we examine the effect of time constraints on stock market participation and trading activity using an identification strategy that exploits COVID quarantine requirements for close contacts of infected individuals. Our results point to time frictions playing a role in limiting stock market participation. These

[2]Other explanations for nonparticipation include household preferences, risks faced by households, and peer effects (Gomes et al. (2021)).

findings complement recent survey and interview evidence from Choi and Robertson (2020) and Duraj et al. (2024), who find that many individuals state the time associated with staying up-to-date with market developments and learning about stocks as a reason for nonparticipation.

We also relate to the literature on retail investor trading behavior. Many studies have observed that investors are slow to rebalance their retirement accounts (Agnew et al. (2003), Choi et al. (2004), Brunnermeier and Nagel (2008)) or investment portfolios (Calvet et al. (2009a)). In comparison to these studies, our study shows that time constraints matter both for the extensive margin (participation decision) and the intensive margin of how much to trade. We show that trading propensity increases sharply when time constraints are relaxed, suggesting that such frictions impede portfolio rebalancing.

Last, we relate to studies on the retail investors' trading activity during the COVID pandemic. Several studies have documented sharp increases in stock market participation and trading during this period (Ozik et al. (2021), Chiah et al. (2022), Greenwood et al. (2023)).[3] We complement these findings by exploiting an identification strategy using COVID self-isolations to analyze the causal effect of the relaxation of time constraints on trading activity.

Our study proceeds as follows. Section 1 describes the data and details of the COVID-19 pandemic in Denmark. Section 2 documents the rise in stock market participation and trading intensity during the pandemic, and highlights that this heightened activity is driven by individuals for whom time constraints are relaxed most. Section 3 describes our identification strategy and lays out our main results on the effect of time on participation. Section 4 explores the heterogeneity of results across investor characteristics and asset classes, and also analyzes the long-term effects of the temporary relaxation in time frictions. Section 5 supplements the analysis with further robustness tests and discussion, while Section 6 concludes.

[3] The increase in trading activity is not restricted to equity markets. For example, trading in cryptocurrency also became more prevalent (Divakaruni and Zimmerman (2024)).

1 Data and institutional details

1.1 Data

We assemble a dataset of Danish individuals aged 20 or over with detailed information on demographics, income, wealth, and their holdings and trading of stocks and mutual funds. We supplement these data with COVID test results at the individual level, as well as data that allow us to identify people who have been in close contact with an infected individual. A key feature of the administrative registers is that they include personal identification numbers (CPR), which are equivalent to the social security numbers in the United States, allowing us to combine different administrative registries made available by Statistics Denmark, as explained below. The majority of the data is assembled for the purpose of individual tax collection or research within medical and social sciences, and is therefore of very high quality.[4]

Income, wealth, and portfolio holdings are from the official records of the Danish tax authorities (SKAT). These data include comprehensive information on individuals' income and wealth at the yearly level. SKAT obtains the data on income and wealth from relevant sources: employers provide statements about the wages paid to their employees, while financial institutions similarly provide information on amounts of deposits, interest received, dividends received, and interest paid. Financial institutions (e.g., brokerage houses and banks) also report portfolio holdings of stocks and mutual funds at an annual frequency and trading of stocks and mutual funds at a daily frequency to SKAT. These data are reported at the individual asset level using International Securities Identification Numbers (ISIN), which allow us to observe the individual securities that investors hold and trade. Our data on income, wealth, portfolio holdings and trading activity cover the period from 2012 to 2022.

Educational records are from the Ministry of Education of Denmark. All completed

[4]The data on income, wealth, and portfolio holdings are comparable to that of other Nordic countries: Sweden (Calvet et al. (2007, 2009a,b)), Finland (Grinblatt and Keloharju (2001), Grinblatt et al. (2012)), and Norway (Døskeland and Hvide (2011), Hvide and Östberg (2015), Fagereng et al. (2017, 2020), Galaasen and Raja (2024)).

years of education, both formal and informal, as well as degree fields, are recorded and made available through Statistics Denmark.

Individual and family data are from the Danish Civil Registration System. These records contain CPRs, gender, date of birth, and CPR numbers of nuclear family members (parents, children, and siblings) and spouses. Importantly, these data also include a unique address ID, which allows us to link individuals who test positive for COVID to individuals who are cohabiting with them, and therefore are in close contact. This allows us to identify individuals that are not infected themselves, but are mandated to be in self-isolation for seven days due to their close contact with an infected individual. We use these plausible exogenous spells of self-isolation to study whether a relaxation of time constraints affects individuals' stock market participation and trading activity.

Individual data on **COVID tests** are from Statens Serum Institut (SSI), which is responsible for the Danish preparedness against infectious diseases under the auspices of the Danish Ministry of Health. The register contains information about COVID tests at the National Test Centers established by the Danish National Board of Health. These data exclude self-administrated antigen tests that become popular in the beginning of 2022. The data record both the date when the COVID test was taken and when the test result was available. Test results are either positive, negative, or inconclusive. COVID tests are either PCR-tests or antigen test, but as our identification strategy focuses on the first waves of COVID, we exclusively rely on the time period where only PCR tests are used. We use these data to identify individuals that test positive for COVID.

In addition to the registry data from Statistics Denmark, we collect data on the availability of COVID tests and rules regarding self-isolation of infected and close contacts from the National Board of Health's website (Sundhedsstyrelsen (2020)).

1.2 COVID-19 timeline in Denmark

In February 2020, the first COVID cases were detected in Denmark.[5] This led to a series of restrictions before a countrywide lockdown starting on March 11th, 2020. The lockdown was gradually lifted, beginning with schools and essential businesses on April 20th, 2020 and ending with social life on May 12th, 2020.

To facilitate the reopening of society, the Danish National Board of Health introduced a new COVID strategy on May 12th, 2020. The strategy included three elements: a mass testing scheme, tracing of close contacts, and home isolation of infected individuals and close contacts.[6] Infected individuals with symptoms were required to be in isolation until 48 hours after symptoms ceased to exist, while asymptomatic infected individuals and close contacts were required to be in isolation for 7 days at home. In addition, close contacts were required to take tests on day 4 and days 6, relative to the time of the contact with the infected individuals.

Subsequently, the Danish National Board of Health introduced different measures related to COVID as cases progressed until the end of January 2022. The most notable restriction was a second lockdown in December 2020, and gradual re-opening of society between March 1st, 2021 and May 21st, 2021. The Danish National Board of Health started to administer COVID vaccines from December 27th, 2021, a program that resulted in an almost fully vaccinated population by the end of 2022.

Overall, the Danish COVID scheme resulted in one of the highest number of tests per capita in the world. The strategy resulted in a rapid expansion of test capacity and introduction of a digital system that allowed individuals to book tests and access test results. Figure A-1 plots the daily number of tests performed for Denmark, Italy, the United Kingdom, and the United States. Testing in Denmark far exceeded that of other countries. By the end of

[5] See SSI's COVID timeline: https://www.ssi.dk/-/media/arkiv/subsites/covid19/presse/tidslinje-over-covid-19/covid-19-tidslinje-for-2020-2022-lang-version---version-1---april-2022.pdf.

[6] Close contacts were defined as individuals that were in close contact with an infected individual for more than 15 minutes.

2020, about 20 tests were being conducted per 1,000 individuals each day, equivalent to 2% of the population, while for the other 3 countries the daily testing rate ranged from 2 to 6 tests per 1,000 individuals.

2 COVID and the rise of stock market participation

The starting point of our analysis is to document the evolution of stock market participation and intensity before and during the COVID pandemic. The goal of this section is twofold: (1) to confirm the rise of stock market participation in Denmark similar to what has been documented for other countries and asset classes (e.g., Ozik et al. (2021), Chiah et al. (2022), Greenwood et al. (2023)), and (2) to highlight that the increase in stock market participation and trade is likely to be associated with the relaxation of time constraints during the pandemic.

2.1 Rise of trading

We first depict the evolution of stock market participation through time and most importantly around the COVID pandemic. Figure A-2 plots the stock market participation rate in Denmark, and shows a gradual decline from 28% in 2012 to 26% in early 2020.[7] During the pandemic, this trend sharply reversed with participation rates reaching 30% in December 2021.[8]

To examine whether the rise in participation is driven by changes in individual characteristics or the unique circumstances of the COVID period, we run the following regression:

$$\text{Participation}_{it} = \alpha + \gamma_t + \beta \cdot X_{it} + \epsilon_{it} \quad (1)$$

[7]The participation rates are comparable to the 25% reported for Finland (Knüpfer et al. (2023)) and the 26% for Norway (Galaasen and Raja (2024)), but lower than the 65% reported for Sweden (Calvet et al. (2009a)).

[8]Figure A-3 plots participation rates for stocks and funds separately. We observe clear increases in participation for both asset classes during the pandemic.

where $\text{Participation}_{it}$ is an indicator equal to one if individual i holds any stock or mutual fund in month t, γ_t is year-month fixed effects, and X_{it} captures individual characteristics. Figure A-4 plots the time fixed effects, γ_t. We see a sharp positive impact on participation coming from the COVID period after controlling for changes in individual characteristics.[9]

To establish whether an intensive margin effect of COVID also exists, Figure A-5 examines the number and value of trades around COVID. The average number of trades placed per stock market participant doubled from around 0.5 before the pandemic to 1 in March 2020 (Figure A-5a). In terms of the size of trades, Figure A-5b shows that the average monthly value of trades placed fell during the COVID period, suggesting that smaller trades became more prevalent.

Overall, the rise in trading activities after March 2020 is observed at both the intensive and extensive margin. The sharp increase in participation and trading motivates us to examine trading activity by demographic characteristics in the period around the pandemic.

2.2 Trading by investors' characteristics

A possible explanation for the heightened trading activity is the relaxation of time constraints during the pandemic. If the increase in participation is driven by time constraints, we should observe a stronger effect for individuals for whom the relaxation is presumably larger, such as younger individuals and people without children. We therefore augment Equation 1 by interacting the individual characteristics with a COVID period dummy.

$$\text{Participation}_{it} = \alpha + \gamma_t + \beta \cdot X_{it} + \theta \cdot 1(t \geq 2020\text{M3}) \cdot X_{it} + \epsilon_{it} \tag{2}$$

Figure 1 plots the marginal effect of COVID on participation for a range of individual characteristics. Panel (a) shows that the increasing stock market participation is driven by younger individuals. Young people aged between 20 and 29 are 4 percentage points more

[9] Table A-2 shows the coefficient estimates for the individual characteristics, X_{it}. We find similar relationships between stock market participation and characteristics such as gender, education, income, and wealth found in the literature (see e.g., Vissing-Jorgensen (2002), Campbell (2006), and Calvet et al. (2007)).

likely to participate in the stock market during the pandemic relative to someone aged 50-59. The marginal effect is economically significant given the unconditional participation rate of 26% in Figure A-2.

We also study the impact of children of different ages. We use the age of your youngest child with the baseline group being those without children. From Figure 1b, we see that the positive marginal effect of COVID is driven by individuals without children. The marginal effect on stock market participation is lower for individuals living with children under the age of 14. Interestingly, the negative effect of living with children is relatively modest for babies, and increases to around 1 percentage point in absolute value for children aged between 2 and 8. For ages between 9 and 14 we observe diminishing marginal effects, which turn positive, but statistically insignificant, for individuals living with children of age between 15 and 18. Overall, the marginal effects in Figure 1b are in line with younger children needing more attention than older children, especially as schoolwork became one of the extra parental responsibilities during the different lockdown periods. Similarly, younger individuals were more likely to be students, and so the lockdown could have had a greater impact on time constraints due to fewer household responsibilities. In Figure 1d, we find a positive effect of being furloughed on participation.[10] By not having to work, these individuals saw a sudden increase in their available time, which potentially allowed them to be more active in the stock market. All together, individuals with a greater relaxation of time constraints relative to their prior constraints were indeed more likely to increase their stock market participation.

To supplement the evidence on the marginal effect of age, children and furlough, we also report the effect of other characteristics on participation in Figures 1c and 1d. As expected, higher levels of income are associated with a large marginal impact of COVID on participation. Moreover, single males with higher financial literacy were more likely to start participating in the stock market around the COVID pandemic. The overall evidence on the

[10]In Denmark, as in many other countries, the government introduced a wage compensation package whereby firms could send their employees home on furlough and receive partial compensation from the government for their salaries. See Bess and Darougheh (2021) for further details on this policy.

heterogeneous impact of COVID on individuals' participation status corroborates a premise on the impact of time on trading.

3 Time constraints and trading

While patterns of the overall population around the pandemic highlight a striking rise in stock market participation and intensity due to the relaxation of time constraints, these patterns might be explained by other factors, for example financial constraints or aggregate stock market performance. In this section, we therefore develop our identification strategy to establish a causal relationship between time and trading. We focus on one measure of plausible exogenous variation in time constraints: close contacts of people who test positive for COVID. Close contacts were required to self-isolate for 7 days despite not being ill themselves, thus giving an exogenous shock to one's available time.

3.1 Sample formation

We start by identifying close contacts of individuals testing positive for COVID between May 12^{th}, 2020 and December 6^{th}, 2020. We focus on the first positive case in the household, and distinguish between individuals in the household that test positive and cohabiting adult household members. The latter are considered close contacts, and are required to self-isolate and take a COVID test 4 and 6 days after exposure (Hagemann-Nielsen and Rønn Tofte (2020)). Both of these tests are required to be negative for the self-isolation period to end, in which case the self-isolation period will last 7 days.[11]

This testing and tracing of close contacts allows us to restrict our analysis to individuals whose time constraints were relaxed as they could no longer go out during the week they had to quarantine. While testing and tracing measures were also enforced in 2021 following the second lockdown, home quarantine was not enforced for vaccinated individuals. Given that

[11] As described in Section 1.2, individuals that test positive are required to be in self-isolation for 7 days or until two days after symptoms cedes to exist.

vaccination status is a choice, we therefore focus on 2020 as this is prior to the introduction of the vaccination program in late December 2020.

Table 1 reports the main characteristics of the full population and the close contacts. We also report summary statistics for the matched control group, the formation of which we will describe in detail in Section 3.2. The condition for being in our treatment sample is living with an infected cohabitant, which is more likely to happen when individuals are living with more family members. These individuals are therefore younger than the general population, less likely to participate in the financial market and hold fewer financial assets on average. The treatment and control groups are very similar to each other, with most characteristics showing no statistically significant differences. Where significant differences exist, the differences are economically small. The treatment and control groups are therefore very comparable in nature.

3.2 Methodology

We study the first positive COVID test experienced in a household from May 12$^{\text{th}}$ 2020, when the economy reopened following the first national lockdown, to December 6$^{\text{th}}$ 2020, when the second national lockdown began. By focusing on this window, we are restricting attention to a period when the economy as a whole was open without limits on social interaction, hence being forced to stay at home and isolate is a meaningful shock to time available for trading. A total of 76,852 individuals test positive during this period, of which 76.4% are the first cases in the household. Our treatment group consists of close contacts of the infected person. Such individuals must live with the infected individual, but not test positive themselves, to avoid health factors influencing our findings. We are left with 38,800 treated individuals.

To control for general trends in stock market participation and trading activity, we form a control group consisting of individuals from untreated households. We do an exact matching on age (in 10-year buckets), education, marital status, gender, and municipality. In line with our findings in Section 2.2 which showed that having young children matters, we additionally match on number of children and whether you have a "young" child (defined to be a child aged between 2 and 10 years old inclusive). We also match on participation status (separately for funds and stocks) in the month before 2 weeks prior to the test, as well as whether you traded or not in that month. We then select the 3 closest matches based on financial wealth, but drop any poor matches, which we define to be cases where the difference in financial wealth exceeds 7,500 DKK (=€1,000). We perform robustness checks on this threshold in Section 5.3.

Having established our treatment and control groups, we use an event study specification to analyze the impact of time constraints on trading activity. The econometrics literature has highlighted how staggered treatments combined with heterogeneous treatment effects over time can lead to biased estimates of the average treatment effect on the treated (Goodman-Bacon (2021), Borusyak et al. (2024)). To overcome these concerns, we adopt a "stacked regression" methodology as suggested by Baker et al. (2022).[12] We create separate datasets g for each matched treatment-control group, which we then stack together. As individuals in the control group are selected from households who did not experience a COVID case, all individuals in the control group are "clean" controls (i.e., they do not face a treatment effect themselves during the sample window). We estimate the following specification at the trading day level t:

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-2}^{1} \beta_\tau I_{itg}^{\tau} + u_{itg} \tag{3}$$

where Y_{itg} is an indicator taking the value one when individual i trades on day t in week g. I_{itg}^{τ} is an indicator taking the value one for close contacts of infected individuals if day t belongs to week τ after the infection date, and zero otherwise. The key feature of stacked regressions is the use of dataset-specific fixed effects. In particular, we have dataset-specific unit fixed effects α_{ig}, which saturates any person fixed effects. We also have dataset-specific time fixed effects $\lambda_{\tau g}$. It is important to note that this subsumes any calendar time fixed

[12]This approach has been used in various studies (see e.g., Cengiz et al. (2019); Deshpande and Li (2019)).

effects, as we are looking at variation in trading within a given matched treatment-control group *observed at the same calendar time*. Our coefficients of interest are β_τ, which estimate the impact of quarantine τ weeks after the infection on our outcome of interest Y_{itg} (e.g., whether an individual i made a trade on day t).

3.3 Main analysis

We begin by looking at how trading propensity evolves over the quarantine period. To do this, we define the dependent variable Y_{itg} as an indicator variable equal to one if individual i makes a trade on day t, and zero otherwise. Before showing the full estimation results, we first plot the average unconditional probability of making a trade on a given day separately for the treatment and control groups. Figure 2 shows that prior to the infection, the average propensity of making a trade is very similar for the two groups with no statistical difference. During the quarantine week (0-6 days), the probability of trading rises sharply from 0.17% to 0.21% and becomes significantly higher than the corresponding probability for the control group ($\approx$ 0.18%). When the quarantine period ends (7-13 days), the unconditional probabilities of the two groups converge once again, highlighting how the quarantine week is particularly special. It is noteworthy that the unconditional probability trends upwards over time for both groups, which reflects other reasons why trading increased during the pandemic such as stronger market conditions in the latter half of 2020 and a rising appeal of online trading platforms. This emphasizes the importance of including time fixed effects in the regression specification to control for general time trends, as well as our identification strategy based on plausible variation in time constraints at the individual level.

Table 2 shows the regression estimates from estimating Equation 3. The results reiterate what is shown in the plots of the average unconditional trading propensity, namely that there is a sharp increase in the probability of trading during the quarantine week. In the specification with the full set of fixed effects (Column 4), we find that the probability of making a trade on a given day is 0.035 percentage points higher during the week of quarantine for the close contacts relative to the control group. Given a pre-quarantine average daily probability of trading of 0.18%, this represents an increase in the probability of trading of roughly 20%. All together, our baseline analysis shows that time constraints have an impact on trading activity.

4 Individual characteristics and the nature of trades

In this section, we explore heterogeneity in the effect of time by individual characteristics (Section 4.1) and in the nature of trades (Section 4.2), in particular the types of assets traded. We then study the long-term effects of this temporary loosening of time constraints on future participation and returns (Section 4.3).

4.1 Individuals' characteristics

To further our understanding of time constraints, we estimate Equation 3 separately based on different individual characteristics. As in the analysis of general trends in Section 2.2, we are interested in whether the effect of quarantine is stronger for individuals for whom the relaxation of time constraints is likely to be high. Figure 3 plots the results by age and whether the individual has young children. Coefficients are scaled by the pre-quarantine average probability of trading, and therefore should be interpreted as the relative change in the probability of trading. Panel (a) shows the effect of age. For individuals aged above 30, there is no change in the probability of trading; however, trading propensity rises by about 35% for those aged 20-29. This is in line with Figure 1a, which showed that younger individuals increased their stock market participation more during the pandemic. In Panel (b), we separate the sample based on whether the individual's youngest child is aged between 2 and 10. This is motivated by Figure 1b, which showed that the weakest impact of the COVID period on stock market participation was on people with children of nursery and primary school ages. Those with young children do not experience a rise in trading. This likely reflects the fact that the quarantine did not relax time constraints due to childcare responsibilities, and thus being forced to stay at home has a smaller impact on available time. In line with this interpretation, we also find that those without children exhibit a significant increase in trading probabilities of about 20%.

To further our understanding of the treatment effect, we examine whether the effect is driven by existing investors, new investors, or perhaps a combination of the two? Figure A-6 plots the estimated effect of quarantine relative to pre-quarantine average trading propensities for existing investors and new investors. The economic magnitudes are similar in both cases with both groups increasing their likelihood of trading by about 20%. However, the statistical significance is stronger for existing investors. Note that if we separate prior non-participants into those aged 20-29 and those aged above 30, then we observe a notable and significant increase in entry amongst the younger age group (Figure A-7). Overall, our findings confirm that a relaxation of time constraints affects both the decision to enter, but also the frequency of trading. As such, time frictions can play a role in explaining both limited stock market participation and portfolio inertia.

4.2 Nature of trades

The previous analysis showed that trading propensity increased during the week of quarantine. In this subsection, we analyze the nature of this trading, in particular the types of trades.

We first look at the size of trades. Figure 4 shows the impact of quarantine on the probability of making small versus large trades. A small trade is defined as one where the total value of trades made in a given day is less than 7,000 DKK ($\approx$ \$1,000), whereas large trades exceed 7,000 DKK. While we find insignificant effects on large trades, the probability of a small trade increases by 25% with high statistical significance. Thus, the quarantine period has a stronger effect on smaller trades. This is in line with Figure A-5b, which shows that the average value of trades placed per person was lower during COVID relative to the pre-COVID period.

We then dig more into the types of trades made. First, we separate buy and sell trades in Figure 5. We see increases in both purchases and sells. Second, we analyze whether the increase in trading is coming through trading of individual stocks or funds (Figure 6). The former could suggest an entertainment motive to trading (Kumar (2009)). We find that both asset classes experience more trading, though the increase in the probability of trading a mutual fund ($\approx 40\%$) exceeds that of stocks ($\approx 15\%$). This suggests that the increased trading is not restricted to trading of entertainment-related lottery stocks.

To add further support to the conclusion that recreational trading is unlikely to be driving our findings, we investigate whether conditional on making a trade, the types of trades made by the treatment and control groups differ. One may wonder whether treated individuals trade because they are bored, and therefore are more inclined towards individual stocks. To test this, we divide securities into four categories: OMX Copenhagen 25 stocks (the main index in Denmark), Danish non-OMX stocks, foreign stocks, and funds. Figure 7 reports the fraction of trades individuals make in four asset classes, separately over time and for the two groups. We see little difference in the likelihood of trading assets of a particular type for the treatment and control groups before, during, and after the quarantine period. Together with our earlier findings, this indicates that a relaxation of time constraints increases the probability of trading, but the heightened trading activity is not tilted towards specific asset types. As such, it does not appear that trading preferences are any different for the treatment and control groups conditional on trading.

4.3 Long term effects

Until now, we have focused on the immediate effects of quarantine. A natural question to ask is whether these effects are long-lasting. Figure 8 repeats our baseline analysis but with more pre- and post-quarantine windows. Figure 8a plots the difference in trading propensities between the treatment and control groups over time. We see that there is a persistent positive impact on relative trading propensities after the onset of quarantine that extends well beyond the initial quarantine week. It is only at 7-13 days after the quarantine that there is no difference in trading, but this likely reflects it being the first week following quarantine and suddenly being able to return to normal social activities. Figure 8b confirms these patterns in a regression setup akin to Equation 3.

While the above analysis shows that the impacts extend to the weeks beyond the initial quarantine week, it is interesting to see the implications for longer-term stock market participation. We therefore estimate the following regression at the monthly level t:

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-4}^{12} \beta_\tau I^{\tau}_{itg} + u_{itg} \tag{4}$$

where I^{τ}_{itg} equals one if month t is τ months after the infection date and individual i belongs to the treatment group (i.e., is a close contact), and zero otherwise.

Figure 9 shows the impact of being a close contact and quarantining on the probability of being a stock market participant over the 12 months following the infection. We observe no pre-trends, indicating that the treatment and control groups exhibited similar trends prior to quarantine. Thereafter, there is an increase in the likelihood of being a stock market participant that persists over the following year. By 12 months after the infection, relative participation rates between the close contacts and the control group are 3.5% higher relative to pre-quarantine participation rates.[13] This suggests that even a temporary relaxation of time constraints can have persistent effects on stock market participation. It also implies that the trades made during quarantine do not exhibit short-term and perhaps gambling behavior, but rather a more permanent participation in the stock market.

We then analyze the realized returns of the close contacts. Figure 10 shows the evolution of realized cumulative returns over the 12 months after quarantine. There is a significant

[13]While relative participation rates do not increase in the first month in the baseline figure, we do see a jump in participation at this horizon if we focus on individuals aged 20-29 (Figure A-8). This is in line with the discussion in Section 4.1, where we show that although there is an insignificant effect on trading for former nonparticipants, there is a significant effect for *young* nonparticipants.

negative impact on cumulative returns of 2 percentage points for close contacts relative to their control group. In Figure A-9, we split the portfolio into stocks and mutual funds, and look at the returns for the asset classes separately. The negative return experienced at the portfolio level is completely driven by stocks, suggesting that quarantine-induced trading of individual stocks is not beneficial on average. Instead, for funds, there is no significant difference in realized returns. The key takeaway from this analysis is that while relaxing time constraints can induce more participation, the increased trading activity is associated with lower returns on average, particularly so if investors are active in trading individual stocks.

5 Discussion

5.1 COVID infected individuals

One alternative interpretation of our results is that being a close contact of an individual infected with COVID can have a direct effect on individual preferences. For instance, individuals might reflect on their own life expectancy or adopt a riskier approach to asset allocation. If this is the case, we should observe a positive impact of COVID on their own stock market participation. Figure A-10 looks at the impact on infected individuals. There is a negative marginal impact on the probability of trading even two weeks post infection. Any preference shift related to having a first-hand COVID experience does not seem to prevail for infected individuals. We therefore conclude that the preference channel is unlikely to be driving our results.

5.2 Varying data windows

In Figure A-11, we show the results when using a narrower 4-day interval rather than the 7-day windows used in the baseline. As before, we find no pre-trends, but see a sharp increase in the probability of making a trade by 20% for both the 0-3 and 4-7 days after time intervals.

However, this effect is then nullified at 8-11 days after the infection, which aligns with the end of quarantine and the findings in our baseline estimation.

5.3 Alternative wealth difference cutoffs in matching procedure

As explained in Section 3.2, our baseline matching procedure uses control individuals where the difference in financial wealth between the close contact and the matched control is less than 7,500 DKK (=€1000). This limit is imposed to avoid having low quality matches. In Table A-1, we show that our results are robust to alternative cutoffs. Columns 1, 2, and 3 use cutoffs of 5,000 DKK, 10,000 DKK, and 25,000 DKK, and we observe very similar coefficient estimates. One may be concerned that in using nominal cutoffs, we may be biasing our sample towards lower wealth individuals because high wealth individuals would be less likely to have a match within a nominal range. In Columns 4, 5, and 6, we require that the difference in financial wealth is within 5%, 10%, and 15% of the treated individual's wealth respectively. Again, we find similar results.

6 Conclusion

In this study, we analyze the effect of time constraints on household trading decisions and portfolio rebalancing. Our empirical tests are motivated by the finding in prior literature that individuals exhibit inertia in asset allocation and therefore rarely make active investment decisions. One plausible explanation for inactivity is that individuals shy away from making active decisions because of time constraints. Although time constraints have been proposed as a likely explanation for low participation levels and portfolio inactivity, it is difficult to convincingly identify plausible exogenous variation in time constraints at the individual level.

In this study, we exploit an identification strategy that provides exogenous variation in time constraints due to self-isolation of close contacts of infected individuals during the COVID pandemic. We show that the propensity to trade for close contacts increases by around 20% relative to the baseline probability of trading. The increase in trading activity is positive and statistically significant during and after the quarantine. In further tests, we show that the increasing trading activity is driven by young individuals and individuals without children, for whom quarantine presumably had a smaller impact on time constraints. While the temporary relaxation in time constraints is shown to increase stock market activity even in the longer term, realized returns are on average lower. Overall, our findings provide important insights for the literature on household finance by providing the first causal estimate of the effect of time frictions on stock market participation and portfolio outcomes.

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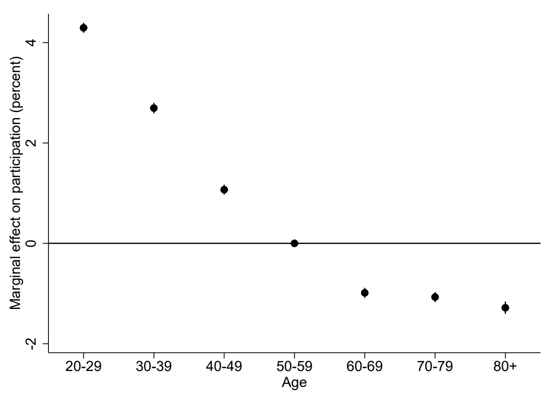
Figure 1: Marginal effects of COVID on stock market participation by individual characteristics

These figures plot the coefficient θ of Equation 2, which captures the marginal impact of the COVID period on stock market participation across different individual characteristics X_{it}.

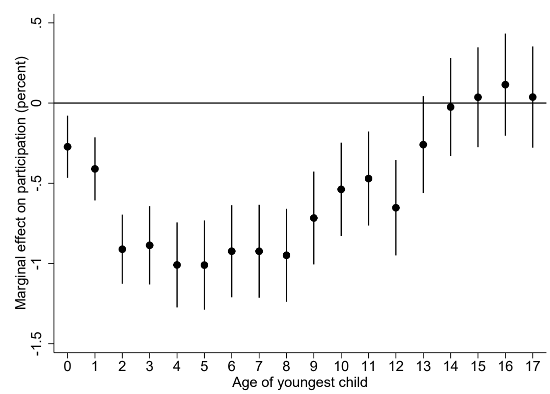
$$\text{Participation}_{it} = \alpha + \gamma_t + \beta \cdot X_{it} + \theta \cdot 1(t \geq 2020\text{M}3) \cdot X_{it} + \epsilon_{it}$$

Panel (a) gives the marginal impact by age (relative to a 50-59 year old), and Panel (b) plots the impact by age of your youngest child who lives with you (relative to an individual with no children aged 17 or below living with you). Panel (c) looks at the marginal effect of income (measured in deciles), with reference group being the 5$^{\text{th}}$ decile. Panel (d) looks at other characteristics. Single male refers to unmarried males. An individual is "financially literate" if they have a university degree in economics, finance, or a related field, or have completed an apprenticeship in the financial industry. "Furlough" equals one if the individual received furlough at any point during March to May 2020, and zero otherwise. 95% confidence intervals are shown.

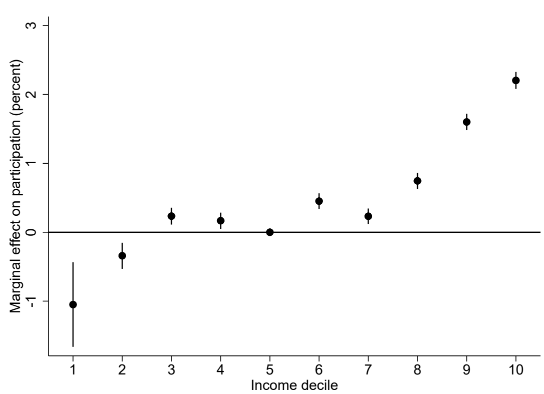
(a) Age



(b) Age of youngest child



(c) Income



(d) Other characteristics

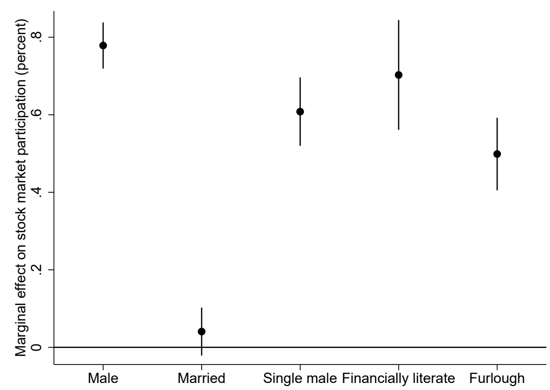


Figure 2: Trading intensity around starting date of home quarantine
This figure plots the average daily probability of making a trade for the close contacts ("treated") and their matched control group separately for different days around the starting date of home quarantine. 95% confidence intervals around the mean are shown.

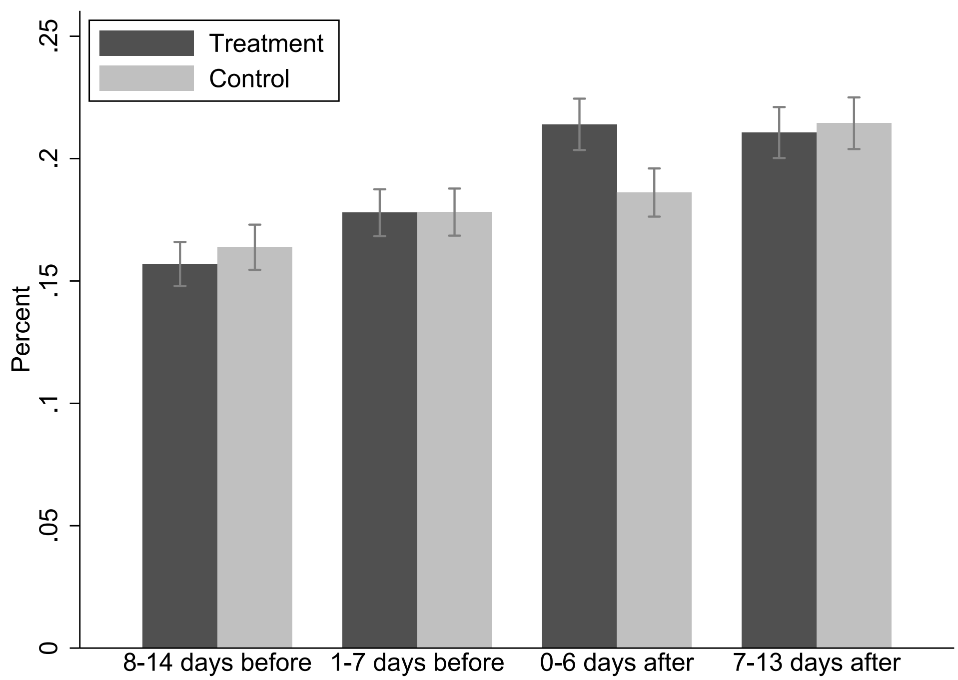


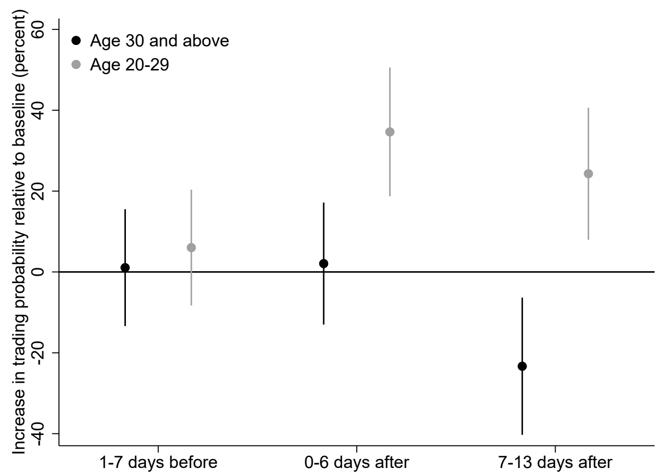
Figure 3: Marginal effects on trading activity around home quarantine by age and children

These figures show the impact of quarantine on trading probabilities of close contacts by own age in Panel (a) and whether the youngest child living with the individual is aged between 2 and 10 inclusive in Panel (b) following estimation of Equation 3 separately by subgroup.

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-2}^{1} \beta_\tau I_{itg}^{\tau} + u_{itg}$$

where Y_{itg} is an indicator taking the value one when individual i trades on day t in week g. I_{itg}^{τ} is an indicator taking the value one for close contacts of infected individuals if day t belongs to week τ after the infection date, and zero otherwise. Scaled coefficients are plotted (scaled by pre-quarantine average propensity to trade for that subgroup) such that the plots show the relative change in the propensity to trade for that subgroup. For example, a scaled coefficient of 20% at "0-6 days after" tells us that close contacts increased their probability of trading by 20% during the quarantine week relative to their matched control group. The reference period is 8–14 days before the infection. 95% confidence intervals are shown.

(a) Age



(b) Children

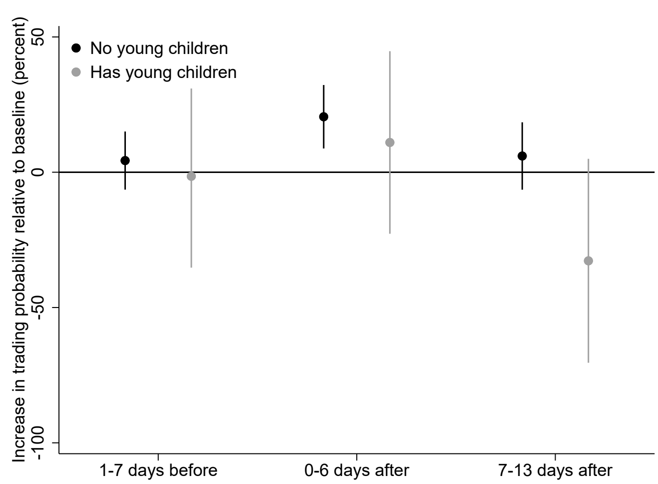


Figure 4: Marginal effects on trading activity around home quarantine by trade size

This figure shows the impact of quarantine on trading probabilities of close contacts separately by size of trade. We distinguish between large trades, which we define to be trades exceeding 7,000 DKK ($\approx$ \$1,000), and small trades, which are trades of value below 7,000 DKK. We estimate Equation 3 separately by the trade size group:

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-2}^{1} \beta_\tau I_{itg}^{\tau} + u_{itg}$$

where Y_{itg} is an indicator taking the value one when individual i trades on day t in week g. I_{itg}^{τ} is an indicator taking the value one for close contacts of infected individuals if day t belongs to week τ after the infection date, and zero otherwise. Scaled coefficients are plotted (scaled by pre-quarantine average propensity to trade for that trade size group) such that the plots show the relative change in the propensity to trade. For example, a scaled coefficient of 20% at "0-6 days after" tells us that close contacts increased their probability of trading by 20% during the quarantine week relative to their matched control group. The reference period is 8–14 days before the infection. 95% confidence intervals are shown.

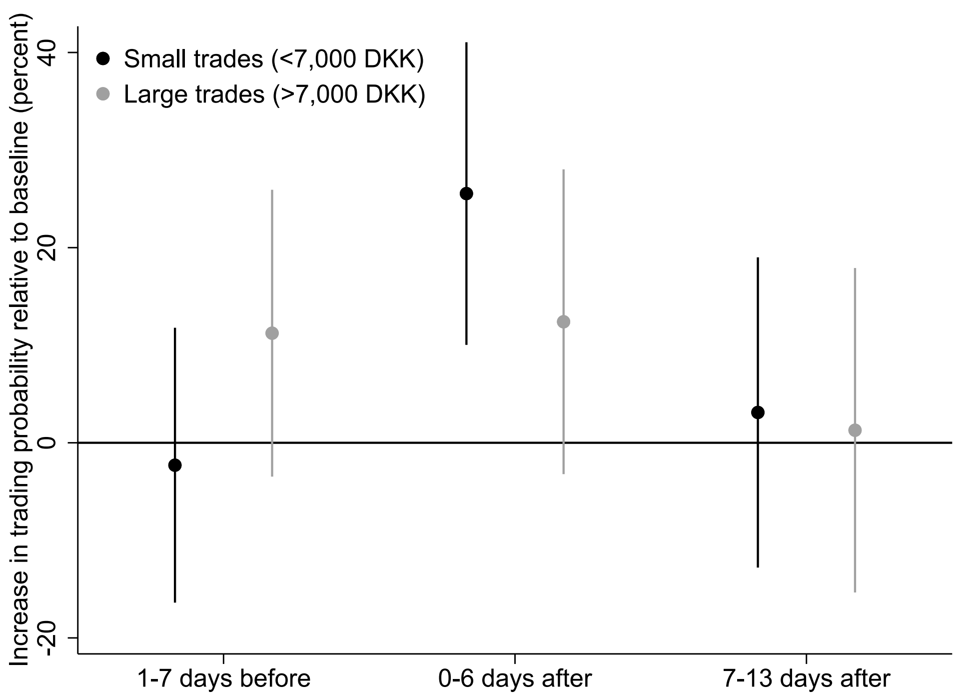


Figure 5: Marginal effects on purchases and sales around home quarantine
This figure shows the impact of quarantine on trading probabilities of close contacts separately for purchases and sales. We estimate Equation 3 separately by the trade type group:

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-2}^{1} \beta_\tau I^\tau_{itg} + u_{itg}$$

where Y_{itg} is an indicator taking the value one when individual i trades on day t in week g. I^τ_{itg} is an indicator taking the value one for close contacts of infected individuals if day t belongs to week τ after the infection date, and zero otherwise. Scaled coefficients are plotted (scaled by pre-quarantine average propensity to trade) such that the plots show the relative change in the propensity to trade. For example, a scaled coefficient of 20% at "0-6 days after" tells us that close contacts increased their probability of trading by 20% during the quarantine week relative to their matched control group. The reference period is 8–14 days before the infection. 95% confidence intervals are shown.

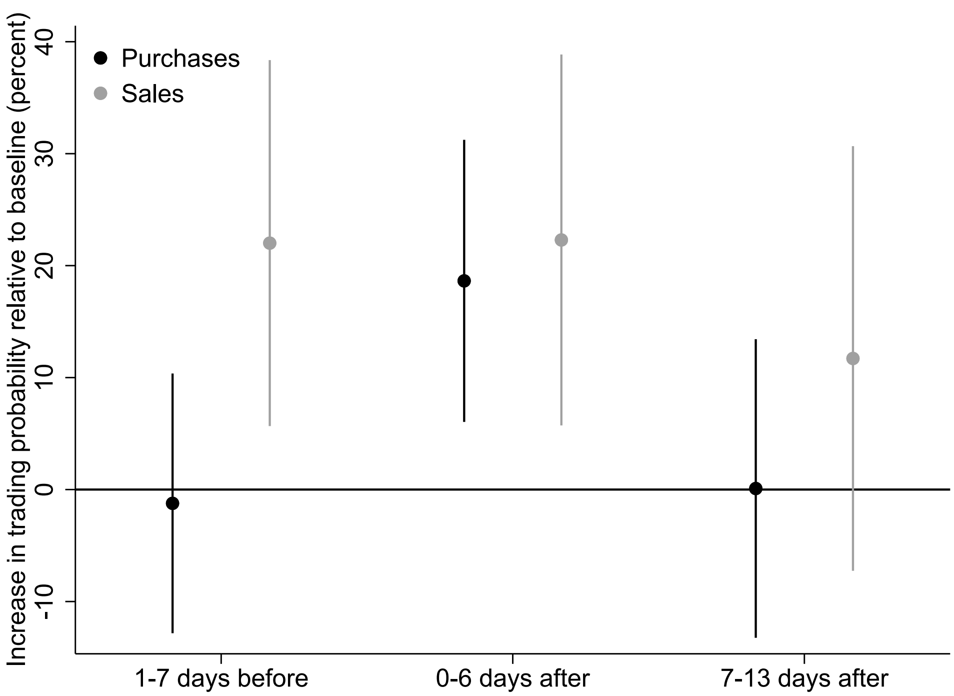


Figure 6: Marginal effects on trading of stocks and mutual funds around home quarantine

This figure shows the impact of quarantine on trading probabilities of close contacts separately for trading of individual stocks and mutual funds. We estimate Equation 3 separately by asset class:

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-2}^{1} \beta_\tau I_{itg}^{\tau} + u_{itg}$$

where Y_{itg} is an indicator taking the value one when individual i trades on day t in week g. I_{itg}^{τ} is an indicator taking the value one for close contacts of infected individuals if day t belongs to week τ after the infection date, and zero otherwise. Scaled coefficients are plotted (scaled by pre-quarantine average propensity to trade) such that the plots show the relative change in the propensity to trade. For example, a scaled coefficient of 20% at "0-6 days after" tells us that close contacts increased their probability of trading by 20% during the quarantine week relative to their matched control group. The reference period is 8–14 days before the infection. 95% confidence intervals are shown.

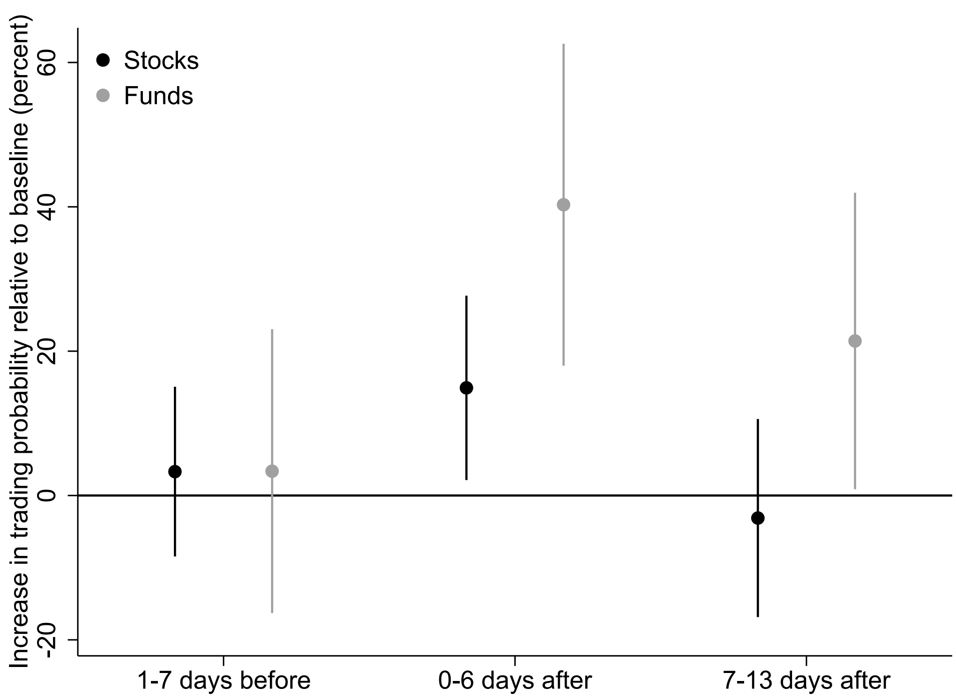
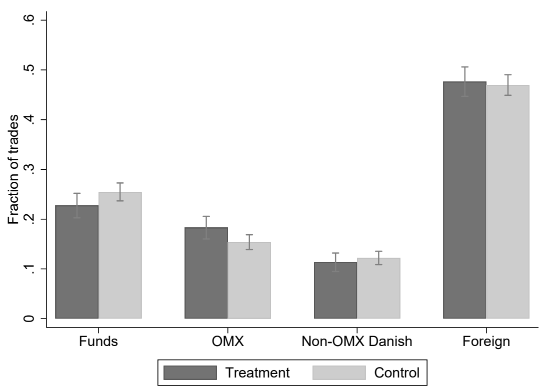
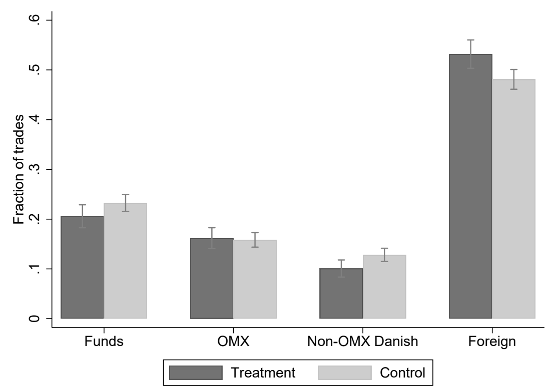


Figure 7: Proportion of trades of different types by time and treatment status
These figures plot the fraction of trades made in different asset classes for the control and treated groups separately. We look at the following asset classes: funds, OMX Copenhagen 25 stocks, other Danish stocks, and foreign stocks. Panels (a) and (b) report fractions of trades 8-13 and 1-7 days before the beginning of quarantine respectively. Panels (c) and (d) look at 0-6 and 7-13 days after the start of the quarantine period respectively.

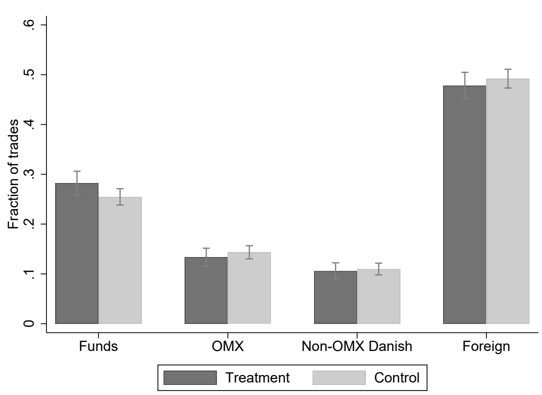
(a) 8-13 days before



(b) 1-7 days before



(c) 0-6 days after



(d) 7-13 days after

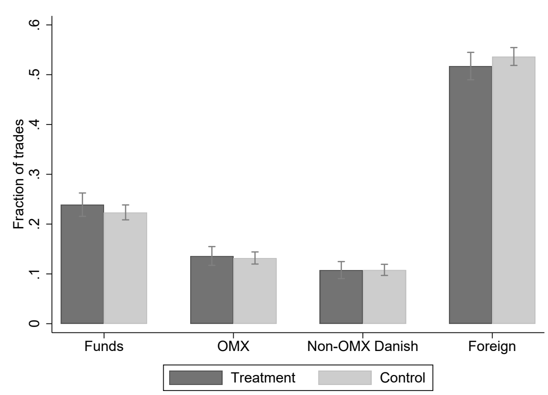


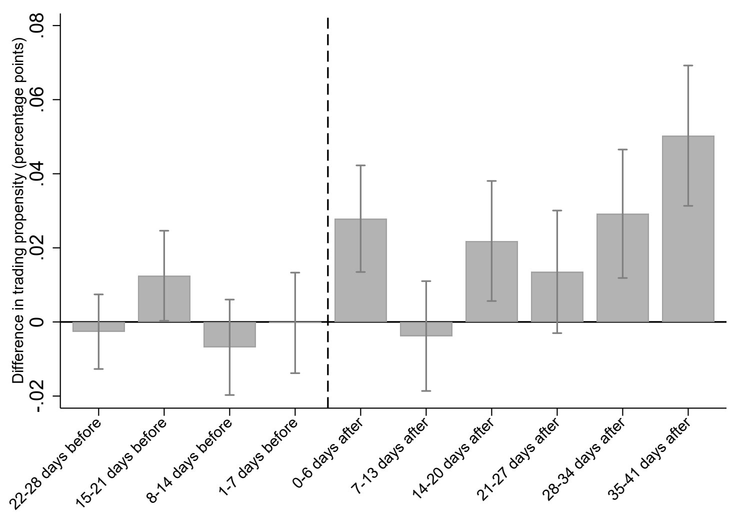
Figure 8: Trading intensity around starting date of home quarantine with additional pre- and post-quarantine windows

Panel (a) plots the difference in trading probabilities between the close contacts ("treated") and their matched control group over different days around the starting date of home quarantine. Panel (b) plots the regression coefficients following estimation of Equation 3 with more windows.

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-4}^{6} \beta_\tau I_{itg}^{\tau} + u_{itg}$$

where Y_{itg} is an indicator taking the value one when individual i trades on day t in week g. I_{itg}^{τ} is an indicator taking the value one for close contacts of infected individuals if day t belongs to week τ after the infection date, and zero otherwise. Scaled coefficients are plotted (scaled by pre-quarantine average propensity to trade) such that the plots show the relative change in the propensity to trade for that subgroup. The reference period is 22-28 days before infection. 95% confidence intervals are shown.

(a) Difference in average trading propensity



(b) Regression with additional windows

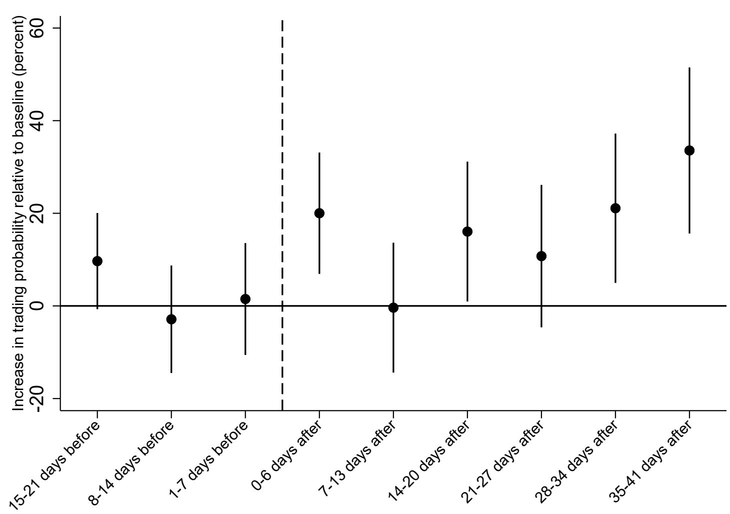


Figure 9: Long-term effect on stock market participation

This figure shows the impact of a quarantining close contact on the likelihood of being a stock market participant over the following 12 months. We estimate Equation 4:

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-4}^{12} \beta_\tau I_{itg}^{\tau} + u_{itg}$$

where I_{itg}^{τ} equals one if month t is τ months after the infection date and individual i belongs to the treatment group (i.e., is a close contact), and zero otherwise. Month 0 denotes participation status on the infection date, month 1 denotes participation status 1 month (30 days) after the infection date, and so on. For example, a coefficient estimate of 2% at horizon τ means relative participation rates between the close contacts and their matched control group increased by 2% at horizon τ. The reference period is 1 month before infection. 95% confidence intervals are shown.

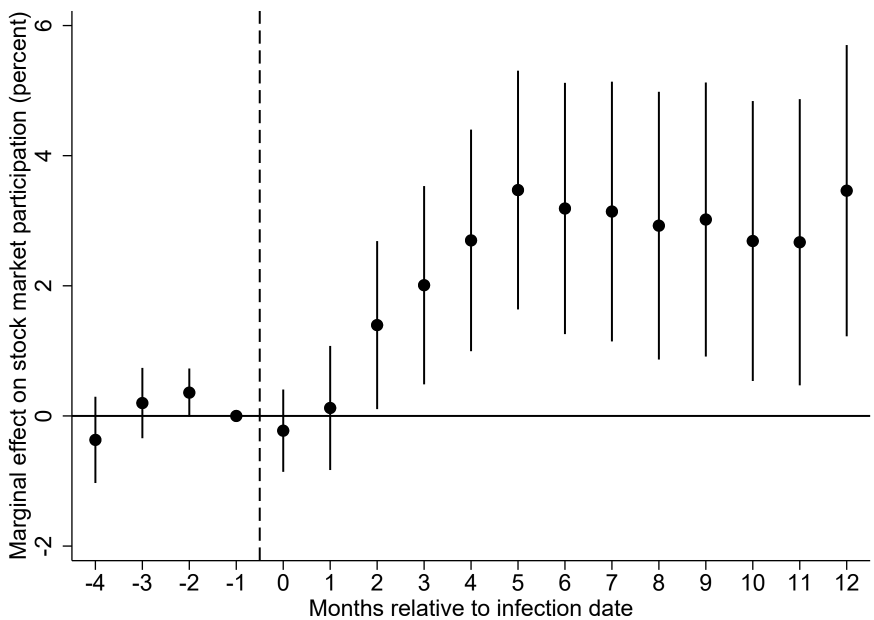


Figure 10: Long-term effect on portfolio returns

This figure shows the impact of a quarantining close contact on realized returns. Returns are cumulative from 4 months prior to the infection. We look at returns conditional on being in the stock market. Returns are based on the full portfolio of the individual (i.e., both stocks and funds). We estimate Equation 4:

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-4}^{12} \beta_\tau I_{itg}^{\tau} + u_{itg}$$

where I_{itg}^{τ} equals one if month t is τ months after the infection date and individual i belongs to the treatment group (i.e., is a close contact), and zero otherwise. Month 0 denotes participation status on the infection date, month 1 denotes participation status 1 month (30 days) after the infection date, and so on. For example, a coefficient estimate of -1 at horizon τ means relative cumulative returns fell by 1 percentage point at horizon τ. The reference period is 1 month before infection. 95% confidence intervals are shown.

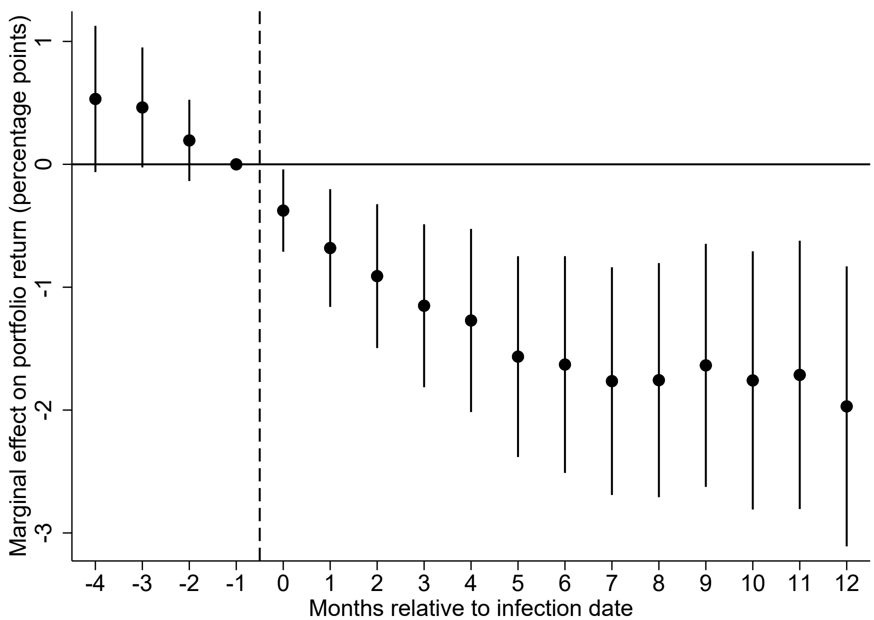


Table 1: Summary statistics

This table shows the mean and standard deviations (in parentheses) of the main attributes of the Danish population in 2020. Column (1) corresponds to the full population aged 20 and above. Columns (2) and (3) correspond to our "treated" COVID close contacts and "control" samples using the methodology explained in Section 3. Column (4) shows the difference in means between the treatment and control groups with t-statistics reported below in parentheses. "Stock market participation" gives the percentage of individuals holding either individual stocks or funds as of January 2020. "Age of youngest child" is the age of your youngest child who lives with you, conditional on having a child in the household (a child is defined to be someone of age 17 or under). An individual is defined to be "financially literate" if they have had some economics or finance education. "Financial assets" refers to the total amount held in both safe and risky financial assets. "Total income" is total personal income excluding capital income. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	(1) All	(2) Close contacts	(3) Control	(4) Difference (2)-(3)
Stock market participation (percent)	25.6	9.1	9.2	-0.1
	(43.7)	(28.7)	(28.9)	(-1.1)
Male (percent)	49.2	50.2	50.2	-0.0
	(50.0)	(50.0)	(50.0)	(-0.0)
Married (percent)	47.8	47.9	47.9	0.0
	(50.0)	(50.0)	(50.0)	(0.0)
Age (years)	51.1	40.8	41.0	-0.2***
	(18.4)	(14.0)	(14.0)	(-3.0)
Age of youngest child (years)	7.3	9.0	8.5	0.6***
	(5.4)	(5.2)	(5.3)	(15.2)
Financial literacy (percent)	3.7	3.3	3.3	0.0
	(18.9)	(17.9)	(17.9)	(0.1)
Financial Assets (1,000 DKK)	360.8	89.4	89.4	0.1
	(17,082.4)	(138.7)	(138.7)	(0.1)
Total Income (1,000 DKK)	360.4	357.2	363.6	-6.4***
	(437.2)	(255.9)	(283.2)	(-5.5)
Number of observations	4,314,148	38,800	101,148	

Table 2: Effect of home quarantine on probability of trading

This table shows the impact of quarantine on the daily probability of trading at different week intervals around the infection date, following estimation of Equation 3.

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-2}^{1} \beta_\tau I_{itg}^{\tau} + u_{itg}$$

where Y_{itg} is an indicator taking the value one when individual i trades on day t in week g. I_{itg}^{τ} is an indicator taking the value one for close contacts of infected individuals if day t belongs to week τ after the infection date, and zero otherwise. The coefficient estimates give the percentage point change in the daily probability of trading in a given week interval relative to the baseline. Column (1) shows the regression results without person or time fixed effects. Columns (2) and (3) add person and time fixed effects to the specification in Column (1), respectively. Column (4) is the full specification including both sets of fixed effects. "Sample mean" is the average pre-quarantine probability of making a trade (in %). Standard errors are clustered at the individual level.

	(1)	(2)	(3)	(4)
8-14 days before	-0.029**			
	(-2.49)			
1-7 days before	-0.008	0.021*	0.000	0.007
	(-0.61)	(1.86)	(0.02)	(0.71)
0-6 days after	0.028**	0.057***	0.029***	0.035***
	(2.06)	(4.56)	(3.01)	(3.46)
7-13 days after	0.025*	0.054***	-0.003	0.004
	(1.78)	(4.07)	(-0.27)	(0.35)
Constant	0.186***	0.171***	0.184***	0.182***
	(33.66)	(45.26)	(41.98)	(58.65)
Sample mean	0.181	0.181	0.181	0.181
Person FE	No	Yes	No	Yes
Time interval FE	No	No	Yes	Yes
N	5,932,080	5,932,080	5,932,080	5,932,080
R-squared	0.00	0.17	0.13	0.22

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix

A-1 Additional tables and figures

Figure A-1: COVID tests performed by country
This figure plots the daily number of COVID tests performed per 1,000 individuals for Denmark, Italy, the United Kingdom, and the United States, from 2020 to 2021. The data is smoothed using a 7-day moving average. Data is obtained from Mathieu et al. (2020).

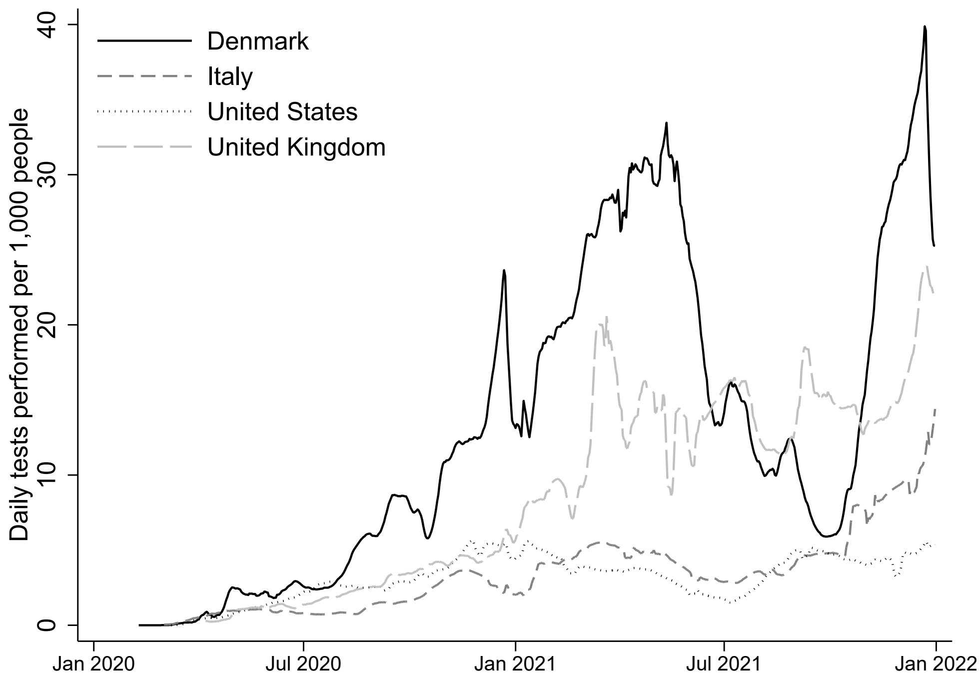


Figure A-2: Stock market participation by month, 2012-2022
This figure plots the stock market participation rate from January 2012 to December 2021 for the Danish adult population (age 20 or above). An individual is defined to be participating if they hold funds and/or stocks. The dashed vertical lines represent the onset of COVID and the first lockdown (March 2020), the December 2020 lockdown and the brief lockdown in December 2021 due to the Omicron variant.

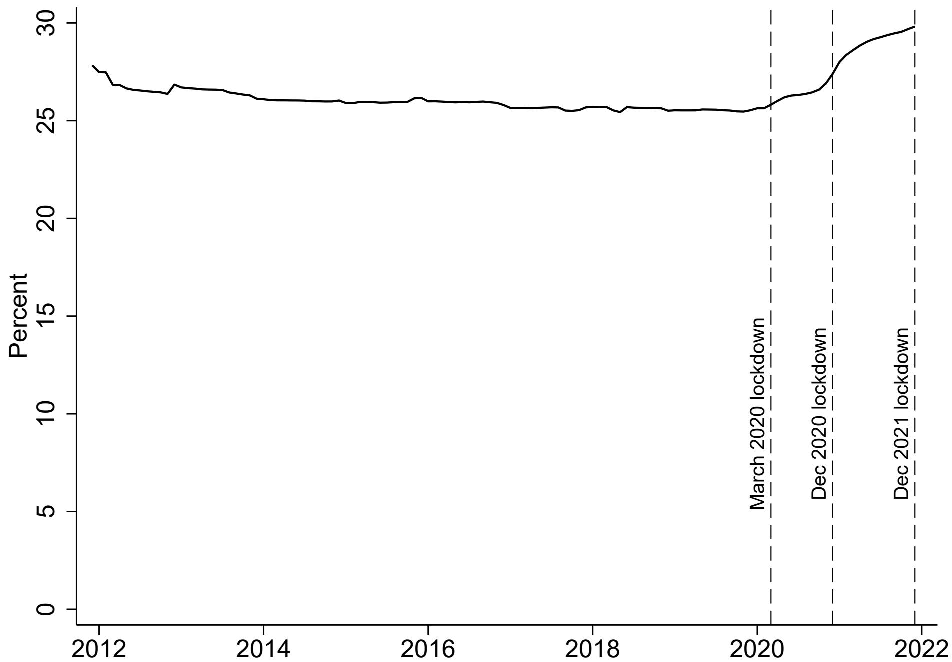


Figure A-3: Stock market participation by asset class by month, 2012-2022
This figure plots the participation rate for the Danish adult population (age 20 or above) separately for individual stocks and funds. Participation rates are plotted for the period from January 2012 to December 2021. The dashed vertical lines represent the onset of COVID and the first lockdown (March 2020), the December 2020 lockdown and the brief lockdown in December 2021 due to the Omicron variant.

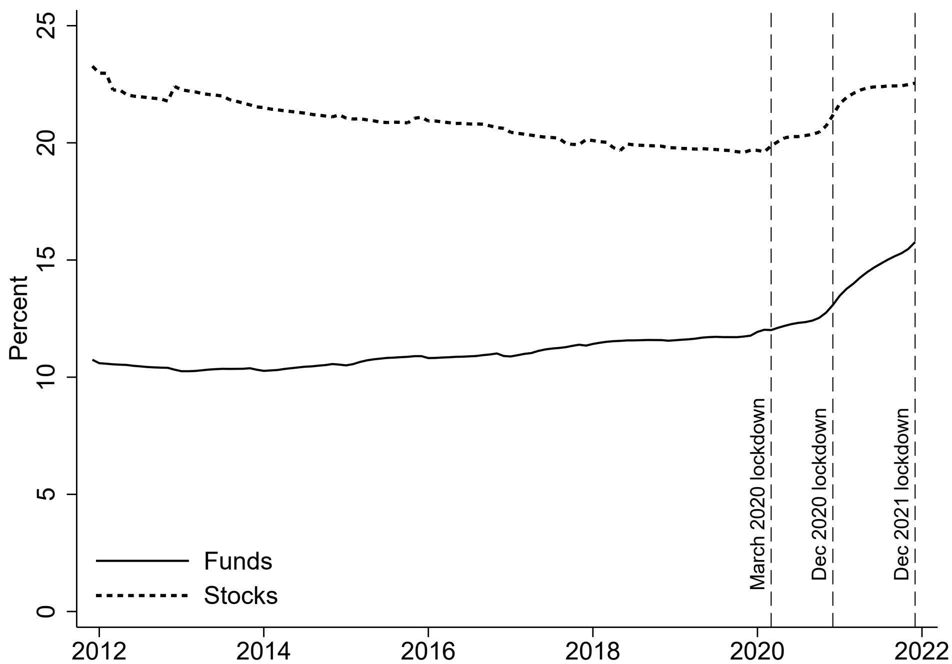


Figure A-4: Marginal impact of calendar time on stock market participation
This figure plots the time fixed effects from a regression of stock market participation on individual characteristics and time fixed effects (Equation 1). 95% confidence intervals are shown. The dashed vertical lines represent the onset of COVID and the first lockdown (March 2020), the December 2020 lockdown and the brief lockdown in December 2021 due to the Omicron variant.

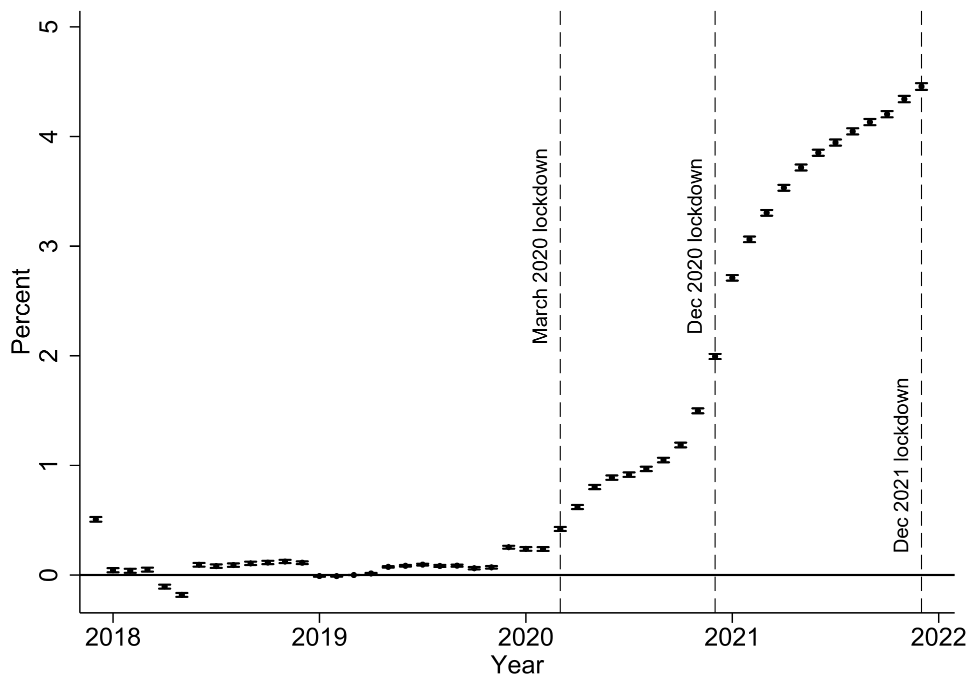
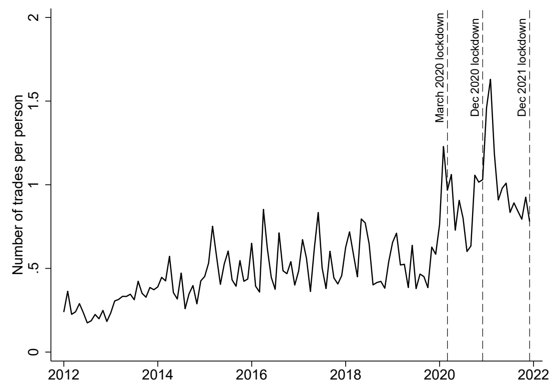
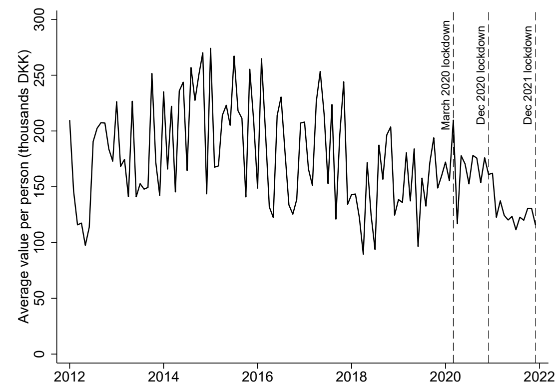


Figure A-5: Trading activity by month, 2012-2021
These figures plot the trading intensity of the adult Danish population from January 2012 to December 2021. Panel (a) plots the average number of trades placed per participating individual in a given month. Panel (b) plots the average value of trades placed over the month per person conditional on making at least one trade. Values are winsorized at the 1st and 99th percentiles before averaging. Panels (c) and (d) plot the aggregate number and value of trades placed over the population. The dashed vertical lines represent the onset of COVID and the first lockdown (March 2020), the December 2020 lockdown, and the brief lockdown in December 2021 due to the Omicron variant.

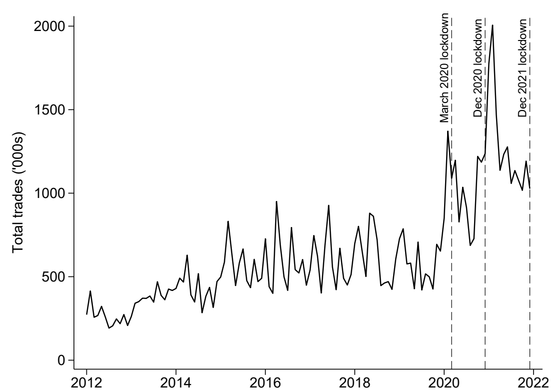
(a) Average number of trades



(b) Average trading value



(c) Total trades



(d) Total value

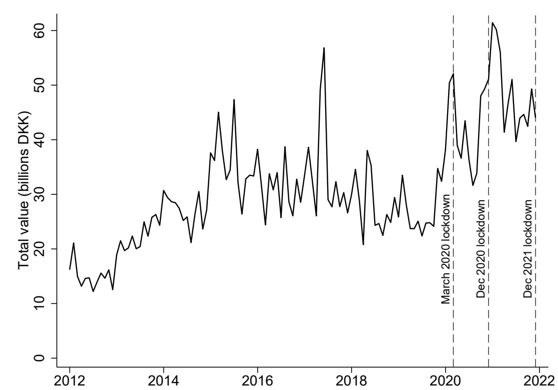


Figure A-6: Marginal effects on trading activity around home quarantine by past participation status

This figure shows the impact of quarantine on trading probabilities separately by the participation status of the individual prior to the infection date. Participation status is measured as of the month before two weeks prior to the infection. We estimate Equation 3 separately by subgroup:

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-2}^{1} \beta_\tau I_{itg}^{\tau} + u_{itg}$$

where Y_{itg} is an indicator taking the value one when individual i trades on day t in week g. I_{itg}^{τ} is an indicator taking the value one for close contacts of infected individuals if day t belongs to week τ after the infection date, and zero otherwise. Scaled coefficients are plotted (scaled by pre-quarantine average propensity to trade for that subgroup) such that the plots show the relative change in the propensity to trade for that subgroup. For example, a scaled coefficient of 20% at "0-6 days after" tells us that close contacts increased their probability of trading by 20% during the quarantine week relative to their matched control group. The reference period is 8–14 days before the infection. 95% confidence intervals are shown.

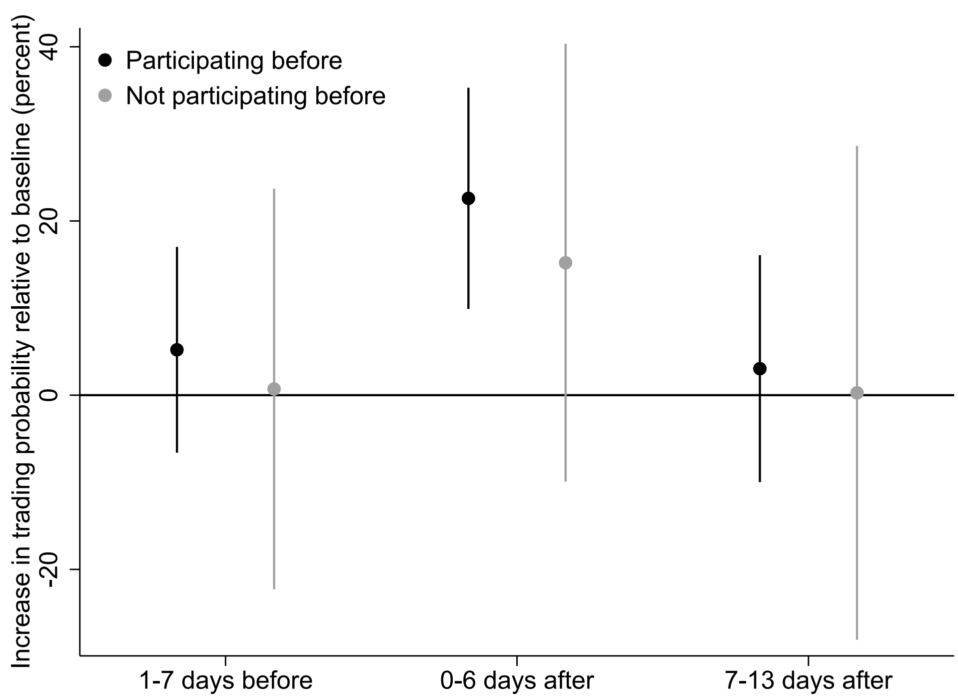


Figure A-7: Marginal effects on trading activity by age for former nonparticipants around home quarantine
This figure shows the impact of quarantine on trading probabilities for prior nonparticipants, but separately by age of the individual prior to the infection date. Participation status is measured as of the month before two weeks prior to the infection. We estimate Equation 3 separately by subgroup:

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-2}^{1} \beta_\tau I_{itg}^\tau + u_{itg}$$

where Y_{itg} is an indicator taking the value one when individual i trades on day t in week g. I_{itg}^τ is an indicator taking the value one for close contacts of infected individuals if day t belongs to week τ after the infection date, and zero otherwise. Scaled coefficients are plotted (scaled by pre-quarantine average propensity to trade for that subgroup) such that the plots show the relative change in the propensity to trade for that subgroup. For example, a scaled coefficient of 20% at "0-6 days after" tells us that close contacts increased their probability of trading by 20% during the quarantine week relative to their matched control group. The reference period is 8–14 days before the infection. 95% confidence intervals are shown.

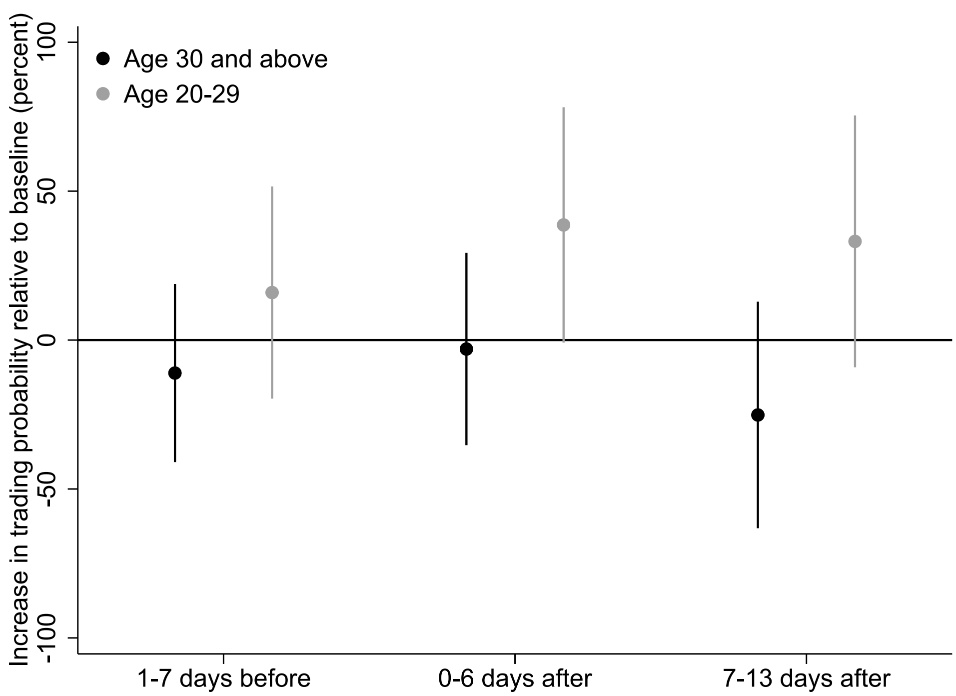


Figure A-8: Long-term effect on stock market participation for those aged 20-29 This figure shows the impact of a quarantining close contact on the likelihood of being a stock market participant over the following 12 months, looking at the sample of people aged 20-29. We estimate Equation 4:

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-4}^{12} \beta_\tau I_{itg}^\tau + u_{itg}$$

where I_{itg}^τ equals one if month t is τ months after the infection date and individual i belongs to the treatment group (i.e., is a close contact), and zero otherwise. Month 0 denotes participation status on the infection date, month 1 denotes participation status 1 month (30 days) after the infection date, and so on. For example, a coefficient estimate of 2% at horizon τ means relative participation rates between the close contacts and their matched control group increased by 2% at horizon τ. The reference period is 1 month before infection. 95% confidence intervals are shown.

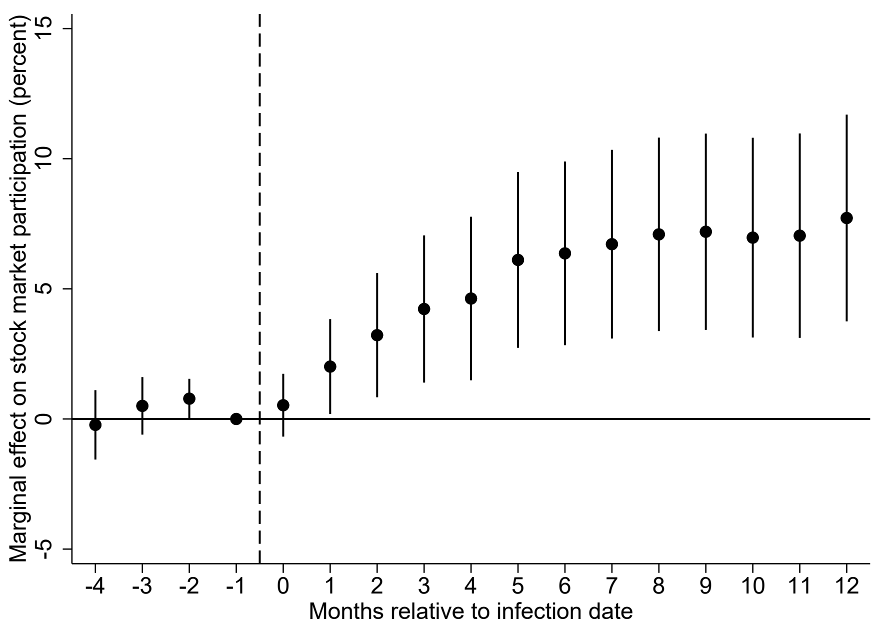


Figure A-9: Long-term effect on portfolio return separately for stocks and funds This figure shows the long-term impact of being a close contact and quarantining on realized returns separately for the fund and stock component of one's portfolio. Returns are cumulative from 4 months prior to the infection. We look at returns conditional on having invested in that asset class. We estimate Equation 4:

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-4}^{12} \beta_\tau I_{itg}^\tau + u_{itg}$$

where I_{itg}^τ equals one if month t is τ months after the infection date and individual i belongs to the treatment group (i.e., is a close contact), and zero otherwise. Month 0 denotes participation status on the infection date, month 1 denotes participation status 1 month (30 days) after the infection date, and so on. For example, a coefficient estimate of -1 at horizon τ means relative cumulative returns fell by 1 percentage point at horizon τ. The reference period is 1 month before infection. 95% confidence intervals are shown.

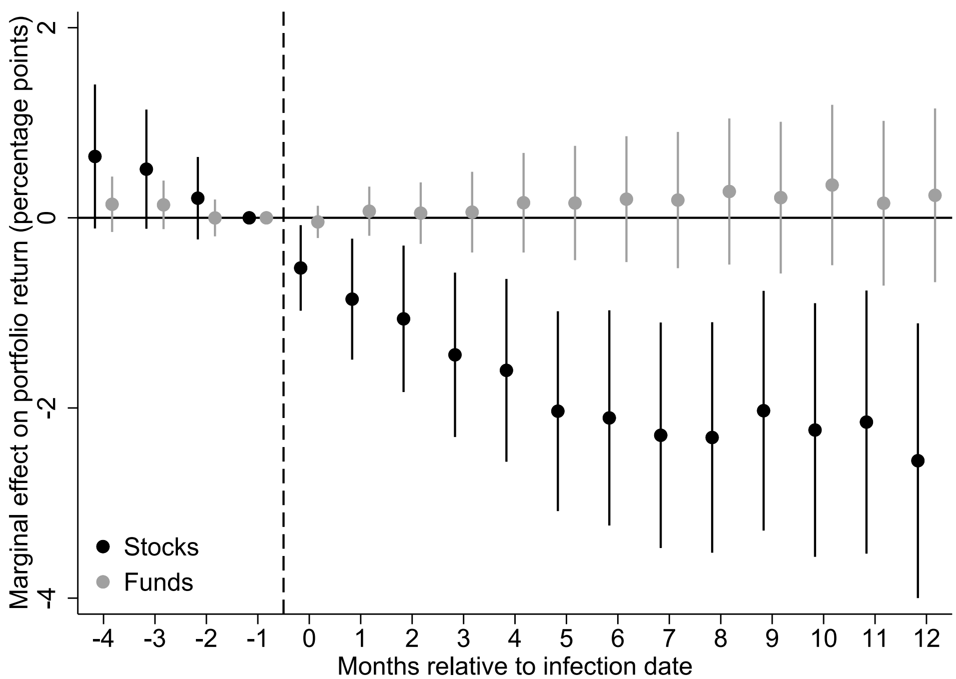


Figure A-10: Marginal effects on trading activity around home quarantine for infected individuals

This figure shows the impact of quarantine on the trading probabilities for the infected individual. We estimate Equation 3:

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-2}^{1} \beta_\tau I_{itg}^\tau + u_{itg}$$

where Y_{itg} is an indicator taking the value one when individual i trades on day t in week g. I_{itg}^τ is an indicator taking the value one for infected individuals if day t belongs to week τ after the infection date, and zero otherwise. Scaled coefficients are plotted (scaled by pre-quarantine average propensity to trade) such that the plots show the relative change in the propensity to trade for that subgroup. For example, a scaled coefficient of 20% at "0-6 days after" tells us that infected individuals increased their probability of trading by 20% during the quarantine week relative to their matched control group. The reference period is 8–14 days before the infection. 95% confidence intervals are shown.

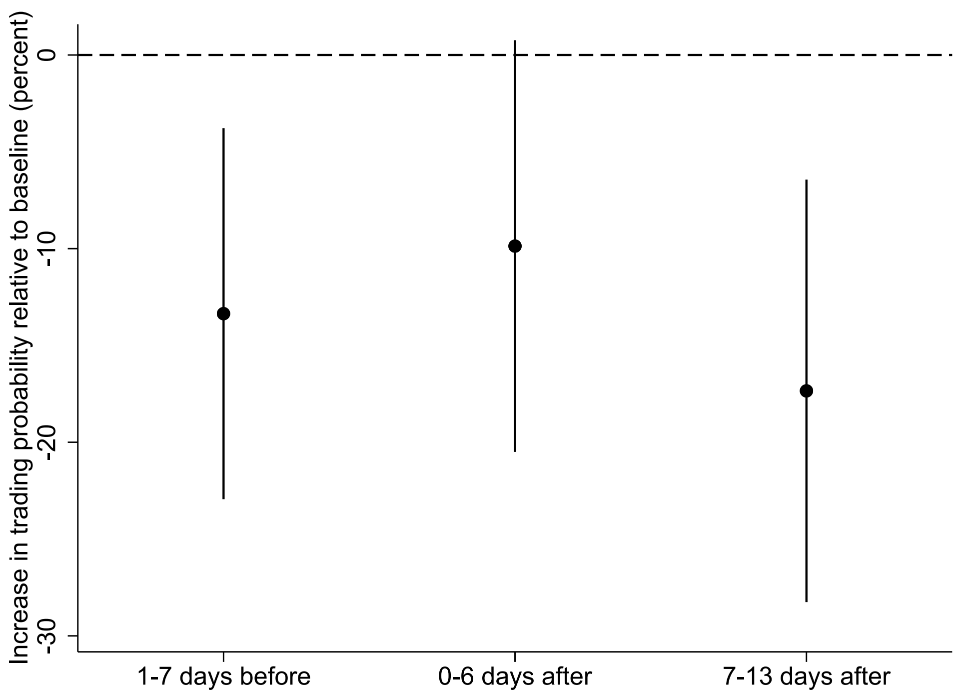


Figure A-11: Marginal effects on trading activity using 4-day window
This figure shows the impact of quarantine on the trading probabilities of close contacts using a 4-day rather than 7-day window around the infection date. We estimate Equation 3 modified to reflect the use of a narrower time window:

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-2}^{2} \beta_\tau I_{itg}^\tau + u_{itg}$$

where Y_{itg} is an indicator taking the value one when individual i trades on day t in window g. I_{itg}^τ is an indicator taking the value one for close contacts of infected individuals if day t belongs to window τ after the infection date, and zero otherwise. Scaled coefficients are plotted (scaled by pre-quarantine average propensity to trade) such that the plots show the relative change in the propensity to trade for that subgroup. For example, a scaled coefficient of 20% at "0-3 days after" tells us that close contacts increased their probability of trading by 20% during this window relative to their matched control group. The reference period is 5–8 days before the infection. 95% confidence intervals are shown.

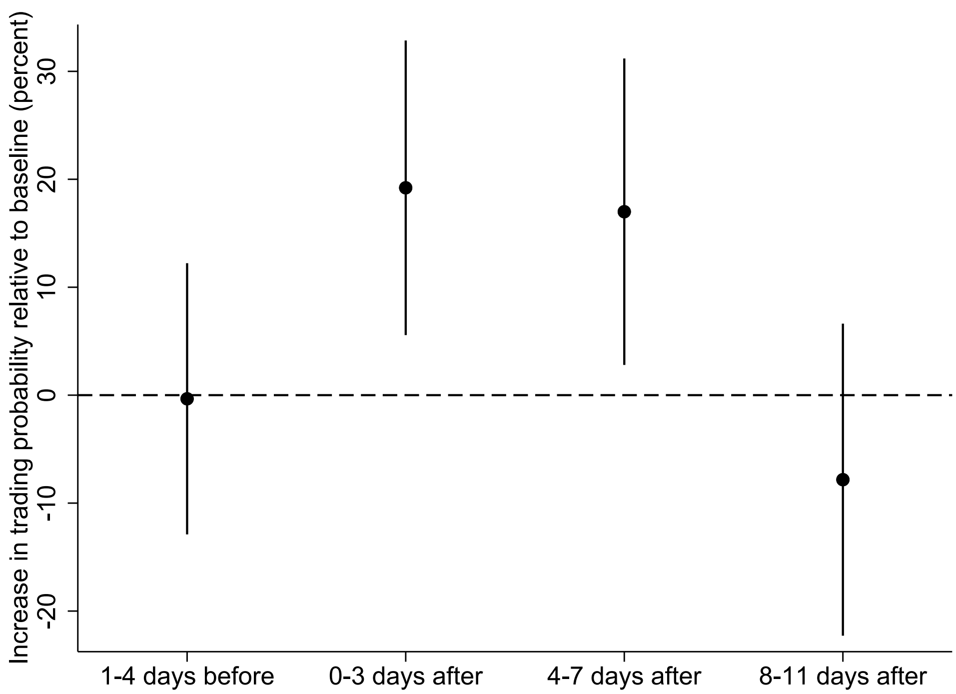


Table A-1: Effect of home quarantine on probability of trading under alternative financial wealth difference cutoffs in matching procedure

This table shows the impact of quarantine on the daily probability of trading at different week intervals around the infection date under alternative cutoffs of financial wealth differences between treated and control individuals. Estimation follows Equation 3.

$$Y_{itg} = \alpha_{ig} + \lambda_{\tau g} + \sum_{\tau=-2}^{1} \beta_\tau I_{itg}^{\tau} + u_{itg}$$

where Y_{itg} is an indicator taking the value one when individual i trades on day t in week g. I_{itg}^{τ} is an indicator taking the value one for close contacts of infected individuals if day t belongs to week τ after the infection date, and zero otherwise. The coefficient estimates give the percentage point change in the daily probability of trading in a given week interval relative to the baseline. Columns (1), (2), and (3) require control individuals to have financial wealth equal to within 5,000 DKK, 10,000 DKK, and 25,000 DKK of the financial wealth of the close contact respectively. Columns (4), (5), and (6) require control individuals to have financial wealth equal to within 5%, 10%, and 15% of the financial wealth of the close contact respectively. "Sample mean" is the average pre-quarantine probability of making a trade (in %). Standard errors are clustered at the individual level.

	(1) $\leq$5k DKK	(2) $\leq$10k DKK	(3) $\leq$25k DKK	(4) $\leq$5%	(5) $\leq$10%	(6) $\leq$15%
1-7 days before	0.004	0.009	-0.003	0.008	-0.001	-0.001
	(0.40)	(0.93)	(-0.29)	(0.70)	(-0.07)	(-0.07)
0-6 days after	0.032***	0.039***	0.032***	0.038***	0.029**	0.031**
	(3.14)	(3.77)	(2.98)	(3.00)	(2.31)	(2.45)
7-13 days after	0.003	0.002	0.005	-0.001	-0.009	-0.008
	(0.27)	(0.22)	(0.40)	(-0.05)	(-0.69)	(-0.61)
Constant	0.173***	0.193***	0.236***	0.254***	0.285***	0.304***
	(55.99)	(61.44)	(70.40)	(66.19)	(75.17)	(79.48)
Sample mean	0.169	0.194	0.236	0.254	0.283	0.304
Person FE	Yes	Yes	Yes	Yes	Yes	Yes
Time interval FE	Yes	Yes	Yes	Yes	Yes	Yes
N	5,558,112	6,180,972	6,868,232	5,400,360	6,267,156	6,705,132
R-squared	0.22	0.22	0.23	0.24	0.24	0.24

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A-2: Impact of individual characteristics on stock market participation
This table reports the marginal impact of individual characteristics on stock market participation following estimation of Equation 1.

$$\text{Participation}_{it} = \alpha + \gamma_t + \beta \cdot X_{it} + \epsilon_{it}$$

"Financially literate" equals 1 if the individual has a university degree in economics, finance, or a related field, or has completed an apprenticeship in the financial industry. "Furlough" equals 1 if the individual received furlough at any point during March to May 2020, and zero otherwise. "Age of youngest child" is the age of the youngest child living with the individual. The baseline group is an individual with no child aged 18 or below living with them. Income and wealth deciles for all months in a given year are based on the end-year reporting from the previous year. We use data from December 2017 to December 2021. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Coefficient	t-statistic
Male	0.034***	(65.42)
Married	0.008***	(16.27)
Single male	-0.004***	(-5.47)
Financially literate	0.131***	(129.79)
Furlough	-0.002*	(-2.46)
Own age		
Age 20-29	0.040***	(69.12)
Age 30-39	-0.002***	(-3.90)
Age 40-49	-0.006***	(-11.89)
Age 50-59	0.000	(.)
Age 60-69	0.023***	(39.74)
Age 70-79	0.078***	(118.38)
Age 80 and above	0.078***	(88.22)
Income decile		
1	0.048***	(19.61)
2	0.008***	(9.62)
3	0.025***	(43.07)
4	0.018***	(35.17)
5	0.000	(.)
6	0.002**	(3.08)
7	0.009***	(17.14)
8	0.018***	(32.21)
9	0.035***	(57.82)
10	0.058***	(85.72)
Fin. wealth decile		
1	-0.108***	(-281.06)

2	-0.074***	(-156.19)
3	-0.063***	(-172.64)
4	-0.037***	(-114.21)
5	0.000	(.)
6	0.046***	(119.29)
7	0.105***	(219.95)
8	0.193***	(350.51)
9	0.340***	(543.66)
10	0.583***	(934.00)
Age of youngest child		
0	-0.013***	(-20.70)
1	-0.007***	(-11.02)
2	-0.007***	(-9.86)
3	-0.007***	(-9.16)
4	-0.004***	(-5.20)
5	-0.003***	(-3.60)
6	-0.001	(-1.21)
7	0.001	(1.18)
8	0.004***	(4.37)
9	0.005***	(6.05)
10	0.005***	(5.92)
11	0.006***	(7.03)
12	0.007***	(7.65)
13	0.006***	(7.29)
14	0.009***	(10.17)
15	0.008***	(9.09)
16	0.009***	(9.83)
17	0.007***	(8.24)
No child aged ¡18	0.000	(.)
Time fixed effects	Yes	
Observations	207935670	
R-squared	0.26	