



# 2138

## Discussion Papers

Deutsches Institut für Wirtschaftsforschung

2025

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#### IMPRESSUM

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ISSN electronic edition 1619-4535

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# Stock Market Participation, Work from Home, and Inequality

Lorenz Meister\*, Lukas Menkhoff†, Carsten Schröder‡

April 9, 2025

## Abstract

Stock market participation among working household heads jumped upwards in 2020 – in Germany by about 25%. A major cause is the required use of work from home (WfH). We show this by adding WfH to a large set of explanatory variables. Moreover, we implement an instrumental variables estimation based on industry-specific levels of WfH-capacity. The transmission channels seem to work via increased available time and time flexibility. Moreover, we show that WfH makes the stock market accessible to a broader population, including lower income groups, which may contribute to lower income inequality in the future.

**Keywords:** stock market participation, work from home, inequality

**JEL codes:** D31, G11, G51

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<sup>0</sup>The authors are grateful for valuable feedback from Cevat Aksoy, Alina Bartscher, Nick Bloom, Charlotte Bartels, Yonatan Berman, Meryem Duygun, Daniel Graeber, Antonia Grohmann, Till Köveker, Anthony Lepinteur, Max Miller, Mikhail Oet, Roy Kouwenberg, and participants at several seminars. Carsten Schröder acknowledges financial support by the German Research Foundation (grant number Schr 1498/7-1).

# 1 Introduction

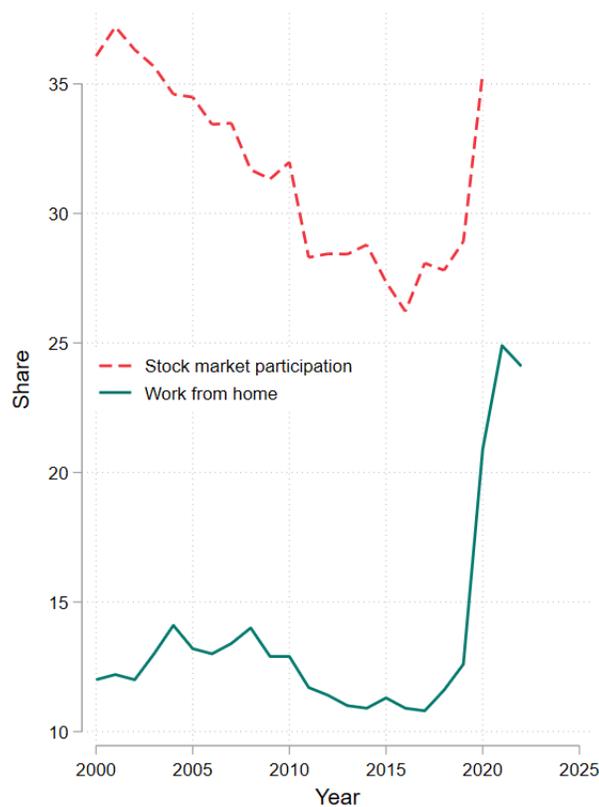
The degree of stock market participation (SMP) is of significant interest for policymakers because it contributes to the dynamics of income inequality in society. One driver of inequality is the systematically higher return on assets that wealthy households earn compared to the general population (Kuhn et al., 2020). A crucial factor behind this advantage is the higher SMP of wealthier households (Bach et al., 2020). In Germany, for example, SMP has averaged 17 percent among all adults since 2010, compared to 59 percent among the top 5 percent and only 13 percent for the bottom 50 percent of the wealth distribution.

These numbers typically change little from year to year, making it noteworthy that SMP increased significantly in 2020, the year Covid-19 was declared a pandemic. In Germany, SMP among working household heads—a subset of the adult population—rose from 28 percent in 2019 to 35 percent in 2020, marking a 25 percent increase (see Figure 1). This surge appears to be persistent and contributed to a broader rise in SMP among all adults, observed in Germany and many other European countries, as discussed in Section 5 (robustness analysis). Such a large increase is rare, as conventional determinants of SMP, such as wealth or education, do not typically change substantially over short periods. Interestingly, this jump coincided with the imposition of work-from-home (WfH) requirements during the Covid-19 pandemic, as shown in Figure 1. This one-time trigger has developed into a permanent “big shift” toward WfH at the expense of onsite work (Barrero et al., 2023). Against this background, we address three questions about the pronounced rise in SMP: First, does WfH emerge as a novel determinant of SMP that helps explain the increase of interest? Second, through what channel does WfH enhance SMP? Third, who are the new stock market entrants, and what are the distributional implications?

We find, for a sample in Germany that is representative for working household heads, and controlling for a comprehensive set of known determinants of SMP, that WfH increases SMP. This effect may explain about one-third of the 2020 surge among this group, so that this effect is just one element among the forces that increased SMP in general. A novel

form of the participation cost channel appears to be at work: WfH reduces commuting time and enhances time flexibility, making it easier to engage in stock market activities. Moreover, SMP's distributional consequences, which are rarely investigated, show that new stock market entrants typically have lower incomes than existing stock owners. This leads to a larger increase in SMP among lower-income groups, contributing to deeper financial inclusion. Thus, WfH serves as a relevant determinant of SMP by relaxing time constraints and may help reduce the gap in asset returns between low- and high-income earners.

Figure 1: Trends in Work from Home and Stock Market Participation



**Notes:** The figure shows time series for stock market participation among working household heads in Germany from the SOEP (dashed red line) and the share of individuals who work from home (solid green line) for the years from 2000 to 2020. There is an abrupt increase in both measures between 2019 and 2020. Source: SOEPv38 and Eurostat.

The shift to WfH is not a new phenomenon, but its widespread adoption during the

pandemic represents a major consequence of contact-reducing policies. Staying at home instead of commuting to the workplace was mandated or recommended in many countries, including Germany, for much of 2020. Employees using WfH saved commuting time and had the opportunity to arrange their private affairs more flexibly. This sudden increase in available and flexible time likely reduced the costs of SMP. It allowed individuals to reflect on their personal finances, improve financial literacy, and open accounts for online stock trading during workdays. Thus, flexible time usage facilitates SMP, complementing other established cost reductions, such as lower transaction fees or increased financial literacy.

One established channel for reducing SMP costs is the reduction in fees, often driven by competition among new suppliers using cheaper technologies. Another channel involves information costs: barriers to entry are lower for individuals with higher education or greater financial literacy. This paper proposes a new cost channel: reducing and relaxing time constraints, which makes it easier to participate in the stock market.

We identify the effect from WfH on SMP for the population of working household heads in Germany. Obviously, other population groups (who do not work) were also affected by policies on social distancing, potentially spent more time at home, and increased their SMP. This may explain why SMP increased more generally in the year 2020. Another particularity of the year 2020 were crisis-related transfers aimed to buffer income losses; without these transfers, SMP would likely have decreased rather than increased. Finally, the year 2020 also witnessed the rise of neobrokers in Germany, offering specialized financial services online only, and thus potentially stimulating SMP through very low trade costs. However, typical neobroker users in this early stage are very different from the working household heads who are our population of interest, as we show in Section 5. We exploit the big shift to WfH in 2020 for our study. Compared to a perfect quasi-experimental setting, the shock is so big that it affects various outcomes simultaneously. We address this endogeneity concern in our identification strategy by controlling for known determinants of SMP in our regressions, and by adding an instrumental variable estimation which is in line with the OLS findings.

To quantify how WfH affects SMP, we use the German Socio-Economic Panel study (SOEP), which annually collects detailed individual and household information. This panel study includes data on risky asset holdings, which serve as a reliable proxy for stock ownership (as shown in Figure 1) and are further discussed in the robustness section below. The SOEP also provides information on respondents' labor market characteristics, including WfH usage, as well as a standard set of socio-demographic variables related to stock holdings, such as wealth and education. To analyze the effect of WfH, we limit the sample to working adults. To better capture individual influence on stockholding, we focus on household heads, as asset holdings are only available at the household level. This selection yields a sample of 6,311 adult individuals who, compared to the overall adult population, have higher education levels, higher incomes, greater wealth, and thus a higher degree of SMP.

Our empirical strategy requires controlling for a comprehensive set of known SMP determinants. In this regard, we align with the approach of Hong et al. (2004), who control for wealth, income, education, race, age, gender, marital status, and risk tolerance to analyze the potential effects of newly introduced indicators such as optimism, openness, and sociability on SMP. We adapt their strategy. The coefficients show the expected, mostly significant signs, and the results remain robust even after including a “work-from-home” variable in any specification.

However, our main approach does not analyze SMP levels directly but instead focuses on changes in SMP by controlling for SMP in the preceding year, following the approach introduced by Bogan (2008). This method reveals that changes in SMP are influenced by conventional determinants, and WfH has a highly significant positive coefficient. Specifically, WfH increases the likelihood of stock market entry by 2.5 percentage points, accounting for approximately one-third of the overall 7 percentage point increase in SMP among working household heads in 2020.

To strengthen the causal interpretation of the positive association between WfH and SMP, we employ an instrumental variable (IV) estimation, as applied in the literature by Hvide

et al. (2024). This approach addresses the possibility of selection bias, as individuals who choose WfH may share unobserved characteristics with those who choose SMP. To address this, we use an instrument based on plausibly exogenous variation: pre-pandemic “work-from-home capacity,” derived from a classification of 100 industry sectors. After controlling for income, wealth, and other factors, this IV approach provides a strong positive impact of WfH on SMP. The significant IV coefficient supports a causal interpretation of WfH’s effect on SMP. However, the IV coefficient is larger than the OLS estimate, likely because the local average treatment effect (LATE) is greater than the average treatment effect (ATE), as is common in the application of instrumental variables. Thus, while the IV estimation confirms a causal effect, the OLS coefficient may be more reliable for estimating the general contribution of WfH to SMP.

To further investigate how WfH may influence SMP, we test the hypothesis that WfH impacts SMP through increased available time (e.g., time saved from commuting) and/or increased flexibility in time usage (see Eliner, 2022). Complementary analyses reveal that indicators such as reduced commuting distance, reduced commuting time, or increased leisure time are positively related to SMP. However, these relationships are neither monotonically increasing nor consistently significant, suggesting that the observed SMP increase is not solely due to time saved from commuting.

If it is not just the quantity of time gained through WfH, the quality of time may also play a role. We find evidence for two specific channels: first, WfH increases SMP only when combined with a flexible work time arrangement, which allows working individuals to better utilize the advantages of WfH. Second, this effect is limited to individuals without children. Working parents are often time-constrained, especially during the pandemic when schools and daycare centers were closed, limiting their ability to benefit fully from WfH.

Examining the potential consequences of increased SMP on inequality trends, as discussed by Favilukis (2013), we compare new stock market entrants to those already participating and those who still do not participate. New entrants typically fall between the two other

groups in terms of wealth, income, and education. Thus, they help broaden the base of stock ownership. Moreover, SMP increases across the income distribution, with the strongest effects among lower-income groups, particularly in the bottom 25% income percentile. However, this effect applies only to lower-income individuals who used WfH. These findings suggest that the WfH-driven increase in SMP contributed to a more equitable distribution of stock holdings. However, due to data limitations, we cannot draw precise conclusions about the amounts of assets held or specific asset allocations.

**Literature.** There is a substantial body of research on SMP and a growing literature on WfH that our study relates to. A crucial aspect of our research is to consider the main known determinants of limited SMP to contextualize the role of WfH. Gomes et al. (2021) classify these determinants into four main categories: household preferences, risks, costs, and peer influence.

(i) Conventional levels of risk aversion alone cannot explain the observed low levels of SMP. Instead, more specific preferences play a role, particularly those that emphasize the frequent downturns in stock returns despite their long-term trend of high risk-adjusted returns. Notable examples include narrow framing (Barberis et al., 2006), ambiguity aversion (Dimmock et al., 2016), and loss aversion (Gomes, 2005), which help explain why many individuals hesitate to hold stocks.

(ii) Certain risks make SMP appear rationally unattractive, such as cases where holding stocks amplifies pre-existing risks, for example, those stemming from labor income (Benzoni et al., 2007). While extreme cases are rare, background risks—those that interact with an individual’s overall risk exposure—often play a role in limiting SMP.

(iii) Costs are frequently considered the primary explanation for low SMP. These include information costs in a broad sense, such as direct financial costs of stock transactions (Bogan, 2008; Hvide et al., 2024), broader participation costs, and general information barriers. Assuming fixed costs for SMP, wealth becomes a key determinant of participation (e.g., Campbell (2006); Cheng et al. (2025)). Socio-demographic factors are also established de-

terminants of SMP (Babenko and Sen, 2014). Strong evidence indicates that higher SMP is driven by financial literacy (Hermansson et al., 2022; Van Rooij et al., 2011), higher education (Black et al., 2018), and high IQ (Grinblatt et al., 2011), which are positively correlated.

(iv) Peer effects significantly influence SMP. These include the positive impact of social interaction (Hong et al., 2004), SMP within the same community (Brown et al., 2008), neighbors realizing high stock returns (Kaustia and Knüpfer, 2012), neighbors with knowledge about stocks (Haliassos et al., 2020), and influences within families (Black et al., 2017).

While this review highlights four main groups of determinants, other factors also influence SMP (see survey by Menkhoff and Westermann, 2024). For instance, SMP tends to be higher among individuals with better health (Rosen and Wu, 2004), greater trust in others (Guiso et al., 2008), more right-leaning political preferences (Kaustia and Torstila, 2011), less children (Yin et al., 2023), and lower exposure to political uncertainty (Agarwal et al., 2022). Early-life exposure to economic crises, such as the Great Depression, also plays a role (Knüpfer et al., 2017; Malmendier and Nagel, 2011).

The recent literature on WfH highlights a significant and enduring “big shift” towards remote work, largely driven by the Covid-19 pandemic (Aksoy et al., 2022). This shift has broad implications, including: (i) Labor Market Dynamics: WfH may lead to potential wage compression, particularly among better-educated and higher-paid remote workers (Barrero et al., 2023). (ii) Productivity: The evidence suggests a mix of effects on productivity (Angelici and Profeta, 2024; Bloom et al., 2015; Choudhury et al., 2024; Gibbs et al., 2023; Ko and Baek, 2025). (iii) Innovation: WfH has been associated with disruptions and changes in innovation processes (Chen et al., 2022). (iv) Consumption Patterns: Remote work influences spatial consumption allocation, as shown in Alipour et al. (2022).

We contribute to the existing literature by expanding the set of potentially important determinants of SMP. Specifically, we incorporate individual risk tolerance as a key preference measure, demographic variables addressing background risk, basic socio-demographic characteristics, and a proxy for sociability. Building on this foundation, we introduce WfH as a new

variable explaining SMP, thereby contributing to the literature on WfH by highlighting another consequence of the “big shift” toward remote work. WfH can alleviate employees’ time constraints, and we provide evidence of the channels through which reduced time constraints associated with WfH can lead to higher SMP.

Please note that this analysis focuses on working household heads, i.e. almost 40% of all households. Within this group, those who use WfH increase their SMP to a significant degree. This determinant explains about one third of these household heads’ increase in SMP, it does not explain the remaining two thirds, or the increase of SMP for working household heads without WfH and for the non-working households. There were obviously also other forces relevant, such as effects from social distancing, the rise of neobrokers or the specific rise of stock markets after March 2020 – these forces are beyond the scope of this paper.

Finally, we address an issue that is rarely explored in the SMP literature—distributional consequences. Our analysis shows that WfH significantly increases SMP among the bottom 25% of the income distribution. Furthermore, we use the Theil Index to measure changes in income inequality within and between four subgroups: stock owners and non-stock owners, stratified by individuals’ WfH status. Our findings indicate that income inequality between stock owners and non-stock owners decreased significantly within the WfH population but not among those who worked onsite. This suggests that WfH enhances access to the stock market for a broader population, enabling lower-income groups to benefit from stock returns.

The paper is structured in five more sections, starting in Section 2 with information about data and in Section 3 informing about methods applied. Section 4 presents results, robustness checks follow in Section 5 and conclusions are provided in Section 6.

## 2 Data

### 2.1 Data base and stock market participation

Our data come from the German Socio-Economic Panel (SOEP), an annual survey of German households, with approximately 15,000 households participating in 2020. We chose the cross-sectional approach, as the item on WfH was not surveyed in the years prior to 2020. To analyze the impact of WfH, we restrict the working sample to employed individuals ("household heads") who are working. This results in a sample size of 5,721 observations.

The SOEP meets the high data demands of the research design by Hong et al. (2004). Furthermore, it enables additional robustness exercises by considering further control variables and complementary analyses of employees' time use. However, the SOEP data has limitations regarding its measure of individual stock holdings in two ways: the precision of the measure of stock holdings and the linkage of stocks to individuals. These limitations necessitate two adjustments, which we briefly explain here, while Section 5 on robustness provides detailed evidence that our procedure does not distort analyses or implications. First, the category most closely approximating stock holdings asks about holdings of risky assets, including stocks, investment funds holding stocks, some risky bonds, or crypto assets, but not real estate or life insurance. Fortunately, stocks dominate this category, and their share remains relatively stable over a few years (see Section 5). Nonetheless, SMP is slightly overestimated. Second, stock holdings are captured at the household level, so we refer to the household head when individual-level information is required. Further analyses show that our results also hold for smaller samples containing only one-person households or subsamples where asset holdings are available at the individual level (again, see Section 5). An overview of all variable definitions is provided in Appendix Table A.1.

## 2.2 Determinants of stock market participation

The literature documents that SMP is robustly linked to a set of individual characteristics, including wealth, income, and education, as well as further socio-demographic variables, such as age, gender, marital status, living in an urban area, migration background, and arguably the most important preference for holding risky assets: risk tolerance. Some U.S.-based studies also consider race as a potential determinant. In our context, we substitute migration background for race, as the latter is relevant in the U.S. but not surveyed in Germany, where the SOEP only asks about migration background—defined as having at least one parent born in another country. Race or migration background may act as proxies for cultural differences or language skills (see Gan et al., 2022).

Moreover, we include variables of “social interaction” in the spirit of Hong et al. (2004), who consider: (i) how often one attends religious services, (ii) how often neighbors are visited, and (iii) how many close neighbors one knows. Regarding these variables, item (i) is directly available in the SOEP, but there is no significant relationship with SMP in the German data. This is likely because the share of people attending religious services in Germany is lower than in the US, has been declining over time, and our working population sample is younger than the one in Hong et al. (2004). Consequently, the primary characteristic of those attending religious services in Germany is a high degree of religiosity, which is negatively correlated with stockholding. Thus, it is unsurprising that the respective coefficient is insignificant in our regressions.

For item (ii), the SOEP includes a related item: how often neighbors and friends are visited. This variable is also insignificant in our analyses. Notably, the coefficient of this variable is much smaller in Hong et al. (2004) (Table III) than those for their other variables, where item (iii) appears to be the best empirical proxy for sociability. For item (iii), the SOEP includes a close substitute: how many close friends one has, which is significantly positive in our regressions. Thus, we include this variable in the main specifications and document results with alternative indicators of sociability in the robustness section.

Since sociability is a specific aspect of personality, it is advisable to control for related traits. In this respect, Hong et al. (2004) discuss three dimensions: they emphasize risk tolerance (as a reverse measure of risk aversion), which is included in our data. They also mention optimism and open-mindedness as important controls, which they approximate. Our dataset contains direct self-reported measures for these variables, including optimism about the future and openness, which is measured based on having new ideas, valuing artistic experiences, being imaginative, and striving for knowledge.

With this approach, we successfully replicate the methodology of Hong et al. (2004) for more recent data, a different country, and a differently defined sample population. Since our data produce results closely comparable to those of Hong et al. (2004), we are confident in using this dataset for our novel analyses, including the integration of WfH as a potential determinant. The survey includes the general question: “Do you ever carry out your work activity at home?”

Table 1 provides descriptive statistics for these variables, indicating a largely representative sample of the working adult population in Germany. Column (1) shows the mean values, column (2) the standard deviation, and columns (3) and (4) the minimum and maximum values, respectively. The degree of SMP in this group is 36%, which is higher than in the overall German population. This is because adults not covered in this sample—such as the young, the elderly, or those without income—are expected to hold stocks less frequently than working adults. Additionally, due to data limitations in the SOEP, stock holdings are recorded at the household rather than the individual level, leading to a higher calculated SMP rate. We demonstrate in the robustness section that this overestimation does not distort our results. Net wealth averages €180,000, equivalent net household income is about €31,407, and the shares of individuals with secondary and tertiary education are 60% and 40%, respectively. The share of individuals aged 35 and younger is 15%, those aged 36 to 60 account for 68%, and those older than 60 constitute the remaining 17% of the sample. Additionally, 49% of the sample is female, 50% is married, 69% live in urban areas, and 18% have a migration

Table 1: Descriptive Statistics: Full Sample

	Full sample				
	(1) mean	(2) sd	(3) min	(4) max	(5) corr
Stock Market Participation	0.36	0.48	0.00	1.00	
Work from home	0.31	0.46	0.00	1.00	0.20
Net Overall Wealth (in mio)	0.18	1.33	-1.84	131	0.09
Equivalent household income	31,407	26,799	10.00	3,360,872	0.15
Primary education	0.01	0.08	0.00	1.00	-0.05
Secondary education	0.60	0.49	0.00	1.00	-0.19
Tertiary education	0.40	0.49	0.00	1.00	0.20
35 years and younger	0.15	0.36	0.00	1.00	-0.02
Between 36 and 60 years	0.68	0.47	0.00	1.00	0.02
Older than 60 years	0.17	0.37	0.00	1.00	-0.00
Female	0.49	0.50	0.00	1.00	-0.11
Married	0.50	0.50	0.00	1.00	0.07
Urban	0.69	0.46	0.00	1.00	0.07
Migration background	0.18	0.38	0.00	1.00	-0.13
Risk tolerance	0.45	0.50	0.00	1.00	0.06
Sociability	0.52	0.50	0.00	1.00	0.07
Optimism	0.83	0.37	0.00	1.00	0.07
Openness	0.53	0.50	0.00	1.00	-0.02
Observations	5,721				5,768

**Notes:** The table depicts the weighted descriptive statistics for the full sample of household heads who are in the working population in the SOEP in 2020. Average stock market participation, measured as the share of individuals who own stocks, is 35%. Column (5) shows correlations between stock market participation and various individual and demographic characteristics. A positive association can be observed for income, education, and age, while there is a negative relation with being female and having a migration background. The sociability indicator is based on the number of close friends that respondents have.

background. Column (5) shows the correlation coefficients for these variables with SMP, which have the expected signs. Table 2 continues the descriptive statistics for subgroups analyzed later in this paper.

Table 2: Descriptive Statistics by Stock Owner Groups

	(1)	(2)	(3)	(4)	(5)
	Old owners	New owners	Non-owners	Old vs. New	Non vs. New
	mean	mean	mean	diff	diff
Stock market participation	1.00	1.00	0.00	0.00	1.00***
Work from home	0.45	0.34	0.24	0.11***	0.10***
Net overall wealth (in mio)	0.33	0.17	0.12	0.16***	0.06***
Equivalent household income	39,114	32,684	27,191	6,429***	5,493***
Income groups					
Top quantile	0.36	0.23	0.14	0.13***	0.09***
Second quantile	0.37	0.33	0.28	0.04	0.05
Third quantile	0.20	0.31	0.33	-0.11***	-0.02
Bottom quantile	0.07	0.12	0.25	-0.05**	-0.12***
Education					
Primary	0	0.01	0.01	-0.01	-0.00
Secondary	0.47	0.53	0.67	-0.06*	-0.14***
Tertiary	0.53	0.46	0.32	0.07*	0.14***
Age groups					
Younger than 35	0.12	0.20	0.15	-0.07*	0.05*
Between 35 and 59	0.72	0.70	0.67	0.01**	0.04
60 and older	0.16	0.10	0.18	0.06	-0.08***
Female	0.43	0.44	0.53	-0.01	-0.09***
Married	0.58	0.48	0.47	0.10*	0.01
Urban	0.71	0.72	0.67	-0.01	0.05*
Migration background	0.12	0.12	0.21	-0.00	-0.09***
Risk tolerance	0.45	0.46	0.44	-0.01	0.01
Sociability	0.56	0.53	0.50	0.02	0.03
Optimism	0.87	0.86	0.81	0.02	0.05**
Openness	0.49	0.52	0.54	-0.03	-0.02
Observations	1,634	591	3,496	2,239	4,099

**Notes:** The table depicts the same statistics for various groups: Individuals that owned stocks in 2019 and 2020 (old owners), individuals that did not own stocks in 2019 but owned stocks in 2020 (new owners), and individuals that did not own stocks in any of the two years (non-owners). Columns (4) and (5) then depict differences between these groups, based on an adjusted Wald test, whereby \* indicates significance at 10%, \*\* indicates significance at 5% and \*\*\* indicates significance at 1%.

### 3 Methods

We explore the role of WfH for SMP using OLS and IV estimations. Following Hong et al. (2004), our baseline OLS regression takes the form:

$$SMP_{ik2020} = \alpha + \beta WfH_{i2020} + \gamma SMP_{i2019} + \mu_k + X_{i2020}\delta + \epsilon_i \quad (1)$$

In equation (1), the dependent variable  $SMP_{ik2020}$  is a dummy indicating whether individual  $i$  in federal state  $k$  owned risky assets in 2020. The coefficient of interest,  $\beta$ , captures how WfH in 2020 alters SMP. Including the prior year’s SMP,  $SMP_{i2019}$ , allows the other coefficients to be interpreted with respect to stock market entrants between 2019 and 2020. We include federal state fixed effects,  $\mu_k$ , and control for a vector of individual characteristics,  $X_{i2020}$ , that is log wealth, log income, years of education, age, gender, marital status, living in an urban or rural area, migration background, risk tolerance, sociability, optimism, and openness. The error term is denoted  $\epsilon_i$ . We also estimate equation 1 as a probit model and find results that are qualitatively consistent with the OLS estimation.

In an ideal experiment, individuals would be randomly assigned to work remotely. Such random treatment assignment would yield a coefficient allowing for a causal interpretation. However, we use observational data. As a result, even after controlling for a large set of individual characteristics and state fixed effects, unobserved factors may simultaneously influence WfH and SMP. To address this, we employ an instrumental variables (IV) strategy.

Our instrument for WfH is the pre-pandemic work-from-home capacity. This industry-level index, provided by Alipour et al. (2023), is based on an item from the 2018 wave of the German BIBB/BAuA Employment Survey, which asks individuals whether they can perform their job from home, assuming their employer allows it. The WfH-capacity is calculated as the share of respondents within an industry who could work from home, aggregated at the NACE industry level. The intuition for this instrument is that individuals’ pre-pandemic capacity to work from home in 2018 (when WfH-capacity was measured) is predictive of

actually working from home in 2020.

The first and second stage estimations of our 2SLS-IV-strategy are as follows:

$$WfH_{ik2020} = \alpha + \phi WfHcapacity_{s2018} + \mu_k + X_{i2020}\delta + v_{is} \quad (2)$$

$$SMP_{ik2020} = \gamma\theta\widehat{WfH}_{i2020} + \rho SMP_{i2019} + \mu_k + X_{i2020}\kappa + \epsilon_{is} \quad (3)$$

where  $WfH_{is2020}$  indicates whether an individual  $i$  in industry  $s$  worked remotely in 2020, while the instrument is denoted  $WfHcapacity_{s2018}$ . The corresponding instrument coefficient  $\phi$  captures the instruments' relevance. The error term is  $v_{ik}$ . In the second stage, the coefficient of interest is  $\theta$ , which indicates the causal effect of WfH on SMP, while we continue to control for the prior year's stock ownership, federal state fixed effects, and individual characteristics.

For consistent IV estimation, several conditions must hold, and they appear to be satisfied here. First, the instrument should be exogenous: we assume that WfH-capacity at the industry level generates exogenous variation in WfH, conditional on individual controls. A potential concern is that, at the industry level, average earnings and education may correlate with WfH-capacity and simultaneously influence WfH and SMP. We address this concern by controlling for education, disposable household income, and net wealth, age, gender, marital status, living in an urban area, migration background, risk tolerance, sociability, optimism, openness, and state fixed effects..

Second, the exclusion restriction implies that WfH-capacity should influence stock market entries only through WfH. This assumption seems plausible, as WfH-capacity reflects industry characteristics that should not directly determine SMP when controlling for education and income. Furthermore, our empirical approach focuses on the change in SMP, which is even less likely to be directly related to WfH-capacity. Third, monotonicity requires that there are no "defiers" (individuals who do not work remotely despite having a high capacity to work from home). Fourth, the instrument must be relevant, as confirmed in the results section.

## 4 Results

### 4.1 Main results

We present the main results step by step. First, we replicate the Hong et al. (2004) baseline specification using our data and confirm that the standard results in the literature are reproduced. The corresponding regression outcome in Table 3, column (1), shows the expected strong association between SMP and wealth, income, and education; in the interpretation of Hong et al. (2004), all these factors contribute to higher SMP. Additionally, other socio-demographic variables are significant: SMP is higher among younger individuals and those living in urban areas but lower among women, married respondents, and those with a migration background. Regarding individual preferences, SMP is higher for respondents who are more risk tolerant, more sociable, and exhibit a higher degree of optimism, while openness has a small negative coefficient. Similar to Hong et al. (2004), we include state fixed effects. Comparing our results to their closest specification (i.e., Table III, “know neighbors,” column 3), we find that even directly comparable coefficients are of similar magnitude: their urban indicator is 0.033, ours is 0.055; their risk tolerance indicator is 0.0311, ours is 0.023; and their sociability indicator is 0.0406, ours is 0.019.

Column (2) shows that WfH has a highly significant coefficient of 0.070, indicating that individuals working from home are 7 percentage points more likely to participate in the stock market. Compared to column (1), the coefficients on education, female, and urban decline, suggesting that part of the impact of WfH was previously absorbed by these variables. Overall, the pattern of coefficients remains largely unchanged, and the  $R^2$  increases slightly, indicating that WfH is a relevant determinant of SMP. In the robustness section, we support this result with two additional analyses: first, we show that WfH had a similar effect in earlier years, meaning that its influence is not specific to 2020. Second, we demonstrate that the result holds when adding the use of “online banking” as a control variable, confirming that WfH does not merely capture the effect of online banking. However, due to significant

Table 3: Main Regression Results

VARIABLES	(1) OLS SMP	(2) OLS SMP	(3) OLS SMP	(4) IV SMP
Work from home		0.070*** (0.015)	0.025** (0.012)	0.127** (0.064)
SMP (first lag)			0.609*** (0.012)	0.605*** (0.011)
Log wealth	0.024*** (0.002)	0.024*** (0.002)	0.008*** (0.002)	0.007*** (0.002)
Log Disposable HH Income	0.146*** (0.013)	0.138*** (0.013)	0.063*** (0.011)	0.049*** (0.016)
Secondary education	0.001 (0.049)	-0.001 (0.048)	-0.017 (0.047)	-0.024 (0.048)
Tertiary education	0.082 (0.050)	0.062 (0.050)	0.011 (0.048)	-0.021 (0.052)
Age	-0.004*** (0.001)	-0.004*** (0.001)	-0.002*** (0.000)	-0.002*** (0.001)
Female	-0.034*** (0.013)	-0.030** (0.013)	-0.021* (0.011)	-0.016** (0.008)
Married	0.003 (0.014)	0.002 (0.014)	0.000 (0.011)	-0.002 (0.010)
Urban	0.055*** (0.014)	0.049*** (0.014)	0.019* (0.011)	0.013 (0.014)
Migration background	-0.129*** (0.016)	-0.123*** (0.016)	-0.065*** (0.014)	-0.054*** (0.012)
Risk tolerant	0.025* (0.013)	0.023* (0.013)	0.005 (0.010)	0.002 (0.010)
Sociability	0.019 (0.013)	0.017 (0.013)	0.016 (0.010)	0.013 (0.009)
Optimism	0.050*** (0.017)	0.050*** (0.017)	0.023* (0.014)	0.024* (0.013)
Openness	-0.035*** (0.013)	-0.039*** (0.013)	-0.004 (0.010)	-0.011 (0.011)
State FE	yes	yes	yes	yes
Constant	-1.310*** (0.129)	-1.228*** (0.130)	-0.485*** (0.111)	-0.352** (0.150)
Observations	5,376	5,376	5,306	5,208
R-squared	0.149	0.152	0.454	0.448

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

**Notes:** The table shows regression results for estimating the main specification from Section 2.3. Column (1) depicts the OLS results of stock market participation in 2020 on various individual characteristics. Column (2) adds WfH as an explanatory variable. Column (3) adds stock ownership in 2019. Finally, column (4) shows the coefficients for a 2-stage-least-squares instrumental variables estimation, whereby WfH is instrumented by WfH-capacity, an indicator at the NACE industry level. Standard errors are also clustered at NACE-level. First stage: A 1-percentage point increase in the WfH-capacity is associated with about a 0.67-percentage point increase in the likelihood of working from home. The F-statistic is 52, thus we are not concerned about any weak instrument bias.

Table 4: First Stage Results

Instruments	WfH
WfH-Capacity	0.67*** (0.11)
Constant	-1.27*** (0.12)
Controls	yes
Observations	5,208
F-statistic	51.63
R-squared	0.25

Robust standard errors in parentheses.

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

**Notes:** The table shows the first stage result that corresponds to the 2SLS-IV specification from Equation 2. WfH-capacity is a relevant instrument. WfH-capacity is defined as the share of employees in each NACE category that indicated in 2018 that they could perform their work from home. An increase of the WfH-capacity by 1 percentage points is associated with 0.67 percentage points higher WfH incidence. The regression controls for log wealth, log income, years of education, age, gender, marital status, urban dummy, migration background, risk aversion, sociability, optimism, openness, and federal state fixed effects, while the respective coefficients are not shown in this table. Standard errors are clustered at the NACE industry level. The second stage is shown in Table 3, column (4).

data loss, this analysis is confined to the robustness section.

In column (3), we include a variable indicating whether the same person held stocks in the previous year. By incorporating lagged SMP, the other coefficients capture stock market entrants between 2019 and 2020, which is the main focus of this research. The results show that lagged SMP is, unsurprisingly, the most significant variable in this specification. Consequently, the other coefficients become much smaller—often only one-half or one-third of their sizes in column (2). Reassuringly, the overall pattern remains consistent, though four of the smaller coefficients (on age, urban, risk tolerance, and optimism) lose their significance. The coefficient size of 2.5 percentage points indicates that approximately one-third of the increase in SMP among working household heads in 2020 can be attributed to required WfH.

Finally, we apply the IV regression introduced earlier in column (4). Due to some missing values for the NACE industry classification (used to match WfH-capacity), the sample size is

reduced to 5,209 observations. Standard errors are clustered at the NACE industry level, as variation from the instrument occurs at this level. The first stage shows that the instrument is significant at the 1% level: a 10-percentage point increase in WfH-capacity is associated with a 6.7-percentage point increase in the likelihood of working from home. First-stage relationships are illustrated as scatterplots in Appendix Figure A.1. The F-statistic is 52, confirming the instrument’s relevance. The IV coefficient indicates that working from home increases the likelihood of stock market entry between 2019 and 2020 by 12.7 percentage points. This coefficient is much larger than the OLS coefficient, likely because it captures the local average treatment effect (LATE, see Imbens and Angrist (1994)). LATE pertains only to individuals who are incentivized by high WfH-capacity to work from home, as analogously argued by ?. Consequently, this coefficient size likely overestimates the general effect of WfH on working household heads, while the OLS coefficient provides a more reliable approximation of the true effect size.

The coefficients on lagged SMP, wealth, income, age, migration background, and optimism remain similar in size and significance, while the coefficient on “urban” loses its marginal significance. Overall, the IV results are consistent with the OLS findings, supporting the main conclusion that WfH is a major determinant of the increase in SMP in 2020.

## 4.2 Transmission channels

An obvious consequence of WfH is the saving of commuting time, which reduces the opportunity costs of SMP. While it can reasonably be expected that saving time contributes to increased SMP, it is less clear whether it is solely the quantity of saved time that matters or whether other circumstances also play a role. Our analysis suggests that circumstances are indeed important. We explore both possible channels—time savings and circumstances—separately.

The time savings from WfH can be estimated using three proxies available in the survey data: changes in commuting distance, commuting time, and leisure time between 2019 and

2020. For each proxy, we divide the total sample into roughly equal-sized groups and estimate the coefficients for WfH separately. For example, for commuting distance, one-third of individuals commuted up to 6 km one way in 2019, another third commuted 7 to 14 km, and the final third commuted 15 km or more. While controlling for all variables in the benchmark regression, Panel A of Figure 2 shows that the coefficients of interest do not vary significantly across commuting distance categories. Thus, there is no consistent pattern indicating that longer commuting distances are associated with a higher degree of SMP.

Thus, it is important to consider that WfH not only reduces commuting time but also provides flexibility in allocating time between work and private life. For example, tasks such as cooking, cleaning, and shopping are no longer confined to post-work hours. This flexibility extends to managing financial affairs: unlike onsite work, WfH allows employees to use private devices for financial transactions, search for market information without interference, and organize finances without colleagues or supervisors nearby. However, the ability to take advantage of this flexibility may depend on individual circumstances.

While such circumstances are often person-specific and difficult to generalize, we analyze the influence of institutional settings, beginning with work time arrangements. The SOEP survey asks participants about their work time arrangement, offering four options: (1) fixed start and end times determined by the firm, (2) varying start and end times determined by the firm, (3) flexible work times where the individual has some control, and (4) completely autonomous work time. Among these, WfH is most likely to improve flexibility when combined with a flexible work time arrangement. In contrast, fixed or autonomous work time arrangements leave little room for improvement in flexibility. Panel B of Figure 2 confirms that WfH increases SMP only when paired with a flexible work time arrangement.

Another relevant circumstance for WfH and SMP is the home environment, particularly in terms of communication and time availability. If a person is alone at home or in a large family, WfH may not facilitate SMP as effectively as in a two-adult household. Indeed, as shown in Appendix Figure A.2, the effect of WfH on SMP is only measurable in two-person

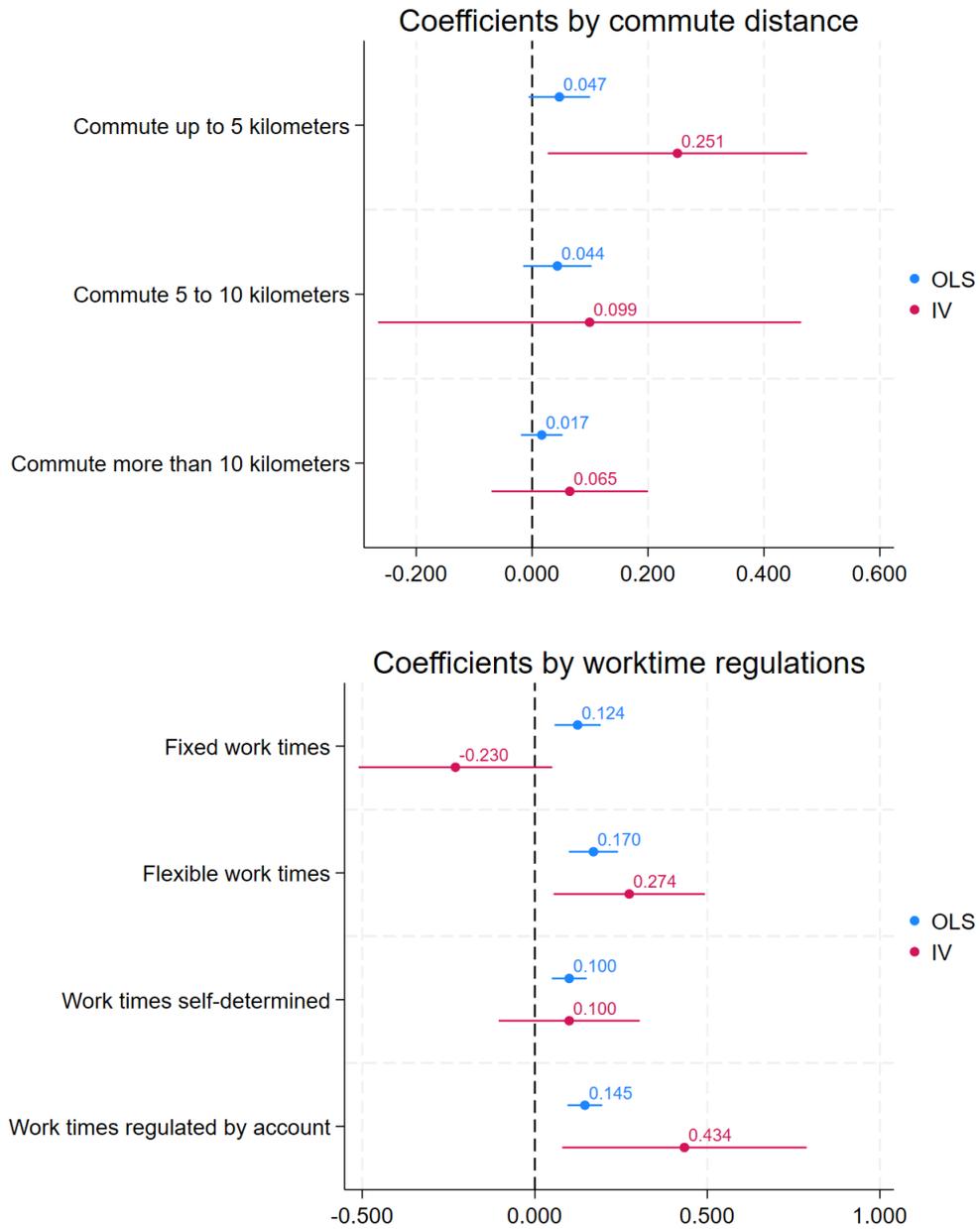


Figure 2: The plot shows coefficients of interest from estimating Equation 1, interacted with different commute distances (Panel A) and work time regulations (Panel B).

households and not in smaller or larger ones. Communication effects can also be considered through sociability, as indicated by the frequency of visiting neighbors. While less sociable individuals (who visit neighbors less than once a month) may experience a greater effect from WfH, the coefficients for sociability are not statistically significant, as shown in Appendix Figure A.3.

A key constraint on time and flexibility is having children at home. The average apartment may lack sufficient space for separate office rooms, making WfH more challenging. In such situations, it is unlikely that time and energy will be allocated to stock market entry. In contrast, singles or couples without children are free from such constraints, making it easier for them to benefit from WfH. This is supported by our data: as shown in Appendix Figure A.4, WfH has a strong effect on SMP in childless households but no effect in households with children.

Further evidence for this comes from the Global Survey of Working Arrangements, where Aksoy et al. (2023) report that, on average, 11% of the 72 minutes of commuting time saved per week is spent on caregiving (8% in Germany). Other main uses of saved time include working (40% globally, 31% in Germany) and leisure (34% globally, 46% in Germany). For households with children, caregiving time increases significantly: women spend an extra 11.4 minutes, and men an extra 9 minutes. While these figures cannot be directly aggregated, they suggest that approximately 25% of saved time in households with children is allocated to caregiving.

Given the strong effect of childless households on SMP, we provide more detail using our standard regression framework. Table 6, columns (1) and (2), contrasts results for childless households versus households with children. For childless households, the coefficients are similar in size and significance to the general sample (see Table 3, column 3). In contrast, for households with children, the coefficient for WfH is very small—about one-sixth of the size for childless households—and statistically insignificant. Another notable difference is the smaller coefficient for “female” in childless households, likely reflecting joint decision-making

Table 5: Households with and without children

VARIABLES	Results by parental status			
	(1) Childless SMP	(2) Parents SMP	(3) Childless IV SMP	(4) Parents IV SMP
Work from home	0.049*** (0.017)	0.003 (0.017)	0.189*** (0.073)	0.080 (0.077)
SMP (first lag)	0.617*** (0.018)	0.605*** (0.018)	0.611*** (0.017)	0.602*** (0.017)
Log wealth	0.005** (0.002)	0.011*** (0.002)	0.003 (0.003)	0.011*** (0.003)
Log Disposable HH Income	0.052*** (0.014)	0.079*** (0.017)	0.039*** (0.015)	0.062*** (0.022)
Secondary education	-0.039 (0.097)	-0.023 (0.061)	-0.039 (0.123)	-0.032 (0.096)
Tertiary education	0.010 (0.098)	-0.007 (0.062)	-0.019 (0.125)	-0.038 (0.100)
Age	-0.002*** (0.001)	-0.002** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)
Female	-0.031** (0.015)	-0.005 (0.016)	-0.025 (0.016)	-0.001 (0.017)
Married	0.004 (0.016)	0.017 (0.018)	-0.002 (0.017)	0.019 (0.018)
Urban	0.015 (0.017)	0.012 (0.015)	-0.001 (0.020)	0.013 (0.016)
Migration background	-0.060*** (0.021)	-0.064*** (0.019)	-0.041* (0.023)	-0.058*** (0.019)
Risk tolerance	-0.007 (0.015)	0.011 (0.015)	-0.013 (0.016)	0.011 (0.015)
Sociability	0.003 (0.015)	0.012 (0.014)	-0.000 (0.015)	0.009 (0.015)
Optimism	0.031* (0.018)	0.020 (0.021)	0.034* (0.020)	0.020 (0.021)
Openness	-0.003 (0.015)	-0.007 (0.014)	-0.014 (0.016)	-0.011 (0.015)
State FE	yes	yes	yes	yes
Constant	-0.329** (0.162)	-0.682*** (0.180)	-0.206 (0.187)	-0.528** (0.224)
Observations	2,518	2,691	2,465	2,649
R-squared	0.460	0.463	0.450	0.458

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

**Notes:** The table shows the results of estimating the main specification and instrumental variables specification from Section 2.3, for childless households (columns 1 and 3) and for households with children (columns 2 and 4). The coefficients of interest indicate that the positive effect of work from home on stock market participation does not hold for households with children, possibly because the effect of relaxing time constraints when not working on-site is not present for this group.

Table 6: Households with and without children

VARIABLES	Results by parental status			
	(1) Childless SMP	(2) Parents SMP	(3) Childless IV SMP	(4) Parents IV SMP
Work from home	0.049*** (0.017)	0.003 (0.017)	0.189*** (0.073)	0.080 (0.077)
SMP (first lag)	0.617*** (0.018)	0.605*** (0.018)	0.611*** (0.017)	0.602*** (0.017)
Log wealth	0.005** (0.002)	0.011*** (0.002)	0.003 (0.003)	0.011*** (0.003)
Log Disposable HH Income	0.052*** (0.014)	0.079*** (0.017)	0.039*** (0.015)	0.062*** (0.022)
Secondary education	-0.039 (0.097)	-0.023 (0.061)	-0.039 (0.123)	-0.032 (0.096)
Tertiary education	0.010 (0.098)	-0.007 (0.062)	-0.019 (0.125)	-0.038 (0.100)
Age	-0.002*** (0.001)	-0.002** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)
Female	-0.031** (0.015)	-0.005 (0.016)	-0.025 (0.016)	-0.001 (0.017)
Married	0.004 (0.016)	0.017 (0.018)	-0.002 (0.017)	0.019 (0.018)
Urban	0.015 (0.017)	0.012 (0.015)	-0.001 (0.020)	0.013 (0.016)
Migration background	-0.060*** (0.021)	-0.064*** (0.019)	-0.041* (0.023)	-0.058*** (0.019)
Risk tolerance	-0.007 (0.015)	0.011 (0.015)	-0.013 (0.016)	0.011 (0.015)
Sociability	0.003 (0.015)	0.012 (0.014)	-0.000 (0.015)	0.009 (0.015)
Optimism	0.031* (0.018)	0.020 (0.021)	0.034* (0.020)	0.020 (0.021)
Openness	-0.003 (0.015)	-0.007 (0.014)	-0.014 (0.016)	-0.011 (0.015)
State FE	yes	yes	yes	yes
Constant	-0.329** (0.162)	-0.682*** (0.180)	-0.206 (0.187)	-0.528** (0.224)
Observations	2,518	2,691	2,465	2,649
R-squared	0.460	0.463	0.450	0.458

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

**Notes:** The table shows the results of estimating the main specification and instrumental variables specification from Section 2.3, for childless households (columns 1 and 3) and for households with children (columns 2 and 4). The coefficients of interest indicate that the positive effect of work from home on stock market participation does not hold for households with children, possibly because the effect of relaxing time constraints when not working on-site is not present for this group.

in households with children, which diminishes gender effects.

Columns (3) and (4) of Table 6 repeat the analysis using the IV estimation. Again, the coefficient for WfH is much larger and statistically significant for childless households, while it remains small and insignificant for households with children. Although the difference between the two groups is smaller than in the OLS regression, it still represents a substantial economic margin. Patterns for other variables largely persist, with some reductions in significance due to the smaller sample size.

Overall, our results suggest that WfH affects SMP through at least two channels. First, WfH saves time, reducing the opportunity costs of SMP. However, this appears to be a necessary but not sufficient condition. Individual circumstances, such as improved time flexibility (e.g., flexible work arrangements) or a childless household environment, are critical for translating the benefits of WfH into stock market entry.

### **4.3 Changes in the composition of stock owners**

The composition of stock owners is crucial in determining which segments of the population benefit from high stock returns. Typically, stock owners are economically better off than non-owners. Table 2 demonstrates that stock owners in 2019 (column 1) were, on average, three times wealthier, had annual household incomes over 12,000 EUR higher, and were better educated compared to non-stock owners (column 3). Those who entered the stock market in 2020 fall somewhere between these two groups, as shown in column 2. This raises the question of whether the shift to WfH not only increased SMP but also made the stock market more accessible to a broader population.

To assess the impact of the shift to WfH in 2020 on the composition of stock owners, we employ two approaches. First, we examine how the effect of WfH on SMP varies across income groups through a split-sample analysis of our main regression. Second, we analyze changes in the income composition of stock owners and non-owners, comparing the WfH and onsite workforces. We use income as a proxy for socioeconomic status due to its detailed

measurement and high correlation with education and wealth.

For the heterogeneity analysis, we categorize households according to their disposable household income into three groups — bottom 25%, middle 50%, and top 25% of the 2020 income distribution — and conduct our main estimation on these separate samples. Results in Table 7 show that the positive association of WfH and SMP is strongest among the lowest income group, indicating that WfH attracted low-income earners to the stock market. This finding is broadly consistent with our instrumental variable (IV) regressions (see Table B.6 in the Appendix).

Next, we investigate whether this mechanism has distributional implications by means of an income inequality decomposition by subgroups, whereby two subgroups are formed based on stock ownership, i.e. stock owners and non-stock owners, respectively. Such a decomposition breaks down overall inequality in two components: (i) inequality within subgroups and (ii) inequality between subgroups – determined by differentials in group-specific mean income (income gaps). If WfH was a relevant factor for narrowing the income gap between stock owners and non-stock owners, we would expect to see such a phenomenon in the WfH population but not among those who continued to work onsite. To decompose income inequality between stock owners and non-owners, we use the Theil index.

The Theil index for a population of size  $i = 1, \dots, I$  is defined as  $T = \frac{1}{I} \sum_{i=1}^I \frac{y_i}{\bar{y}} \ln \left( \frac{y_i}{\bar{y}} \right)$ , where  $y_i > 0$  represents individual income and  $\bar{y}$  is the average income. For a population consisting of non-overlapping groups  $g = 1, \dots, G$ , where  $I_g$  is the group size,  $\bar{y}_g$  is the average group income, and  $s_g = \frac{\bar{y}_g I_g}{\bar{y} I}$  is the group’s share of total income, the Theil index can be rewritten as:

$$T = \sum_{g=1}^G s_g T_g + \sum_{g=1}^G s_g \ln \left( \frac{\bar{y}_g}{\bar{y}} \right) \quad (4)$$

Thus, overall inequality in the population is the sum of two components: within-group inequality, captured by the group-specific Theil indices  $T_g$ , and between-group inequality, determined by the differences in group-specific average incomes  $\bar{y}_g$ . We computed both

Table 7: Split by income groups

VARIABLES	Main Results		
	(1) Bottom25income SMP	(2) Middle50income SMP	(3) Top25income SMP
Work from home	0.081** (0.034)	0.008 (0.017)	0.019 (0.021)
SMP (first lag)	0.627*** (0.043)	0.622*** (0.017)	0.581*** (0.022)
Log Wealth	0.006*** (0.002)	0.009*** (0.002)	0.001 (0.005)
Log Disposable HH Income	-0.026 (0.026)	0.074** (0.037)	0.059*** (0.023)
Secondary education	0.020 (0.053)	-0.029 (0.103)	
Tertiary education	0.017 (0.056)	0.008 (0.103)	0.006 (0.022)
Age	-0.001 (0.001)	-0.003*** (0.001)	-0.002** (0.001)
Female	-0.027 (0.022)	-0.015 (0.015)	-0.036 (0.022)
Married	-0.029 (0.023)	-0.009 (0.015)	0.041* (0.022)
Urban	-0.022 (0.023)	0.027* (0.015)	0.020 (0.024)
Migration background	-0.017 (0.027)	-0.062*** (0.019)	-0.098*** (0.033)
Risk tolerance	0.008 (0.022)	-0.003 (0.014)	0.018 (0.021)
Sociability	0.018 (0.022)	0.005 (0.014)	0.029 (0.020)
Optimism	0.011 (0.028)	0.013 (0.018)	0.051* (0.031)
Openness	0.007 (0.022)	-0.003 (0.014)	-0.011 (0.021)
State FE	yes	yes	yes
Constant	0.303 (0.249)	-0.523 (0.380)	-0.440* (0.244)
Observations	877	2,905	1,525
R-squared	0.383	0.419	0.396

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

**Notes:** The table shows the results for estimating the main specification from Section 2.3 on various income groups: The bottom 25%, middle 50%, and top 25% of the income distribution. Results indicate that there is only a positive and significant association between work from home and stock market participation in the low-income group.

within- and between-group inequality for the entire sample and for WfH and onsite workers separately, using SOEP survey weights to ensure representativeness of the German labor force. We focus on changes in SMP from 2019 to 2020 and its distributional effects, calculating indices for both years and assessing changes over time. To explore the precision of our inequality measures, we use a bootstrap procedure with weights stratified by stock ownership status.

The top panel of Table 8 indicates that both within- and between-group income inequality decreased significantly in the full sample. Specifically, the Theil index was 0.183 in 2019 and fell by 0.015 points to 0.168 in 2020. Income differences between stock owners and non-owners lie at 0.015 points in 2019, thus explaining about 8% of overall inequality. However, the decline of this component to 0.010 in 2020 explains around a third ( $-0.005/-0.015$ ) of the overall inequality decline between 2019 and 2020.

The middle panel of Table 8 on the sample of onsite workers shows different patterns: The Theil index marginally increased from 0.114 to 0.116 from 2019 to 2020, whereby the between-group component remained unchanged at 0.005.

The bottom panel of Table 8 confirms that the reduction in income inequality in the full sample is entirely driven by the WfH-population. The Theil index in this group decreased from 0.252 by 0.034 points to 0.218. An assimilation in incomes between stock owners and non-owners can be observed, as the between-group component more than halved from 0.019 to 0.008. The resulting decrease in between-group inequality among WfH-workers by 0.011 points explains the reduction in between-group inequality in the full sample.

Remarkably, between-group inequality decreased substantially among WfH workers, while it has remained unchanged among onsite workers. This suggests that the composition of stock owners became more diverse among the WfH workforce, consistent with our previous findings.

In summary, the increase in SMP has led to broader participation in the stock market. The specific role of WfH is noteworthy, as it appears to have broadened stock ownership among lower-income groups. This suggests that WfH has facilitated increased SMP for these

Table 8: Changes in income inequality between stock owners

Sample	Type	Theil Indices		
		2019	2020	Diff
Full sample	Overall	.183 (.022)	.168 (.012)	-.015 (0.000)
	Between-group	.015 (.003)	.010 (.002)	-.005 (0.000)
Onsite workers	Overall	.114 (.008)	.116 (.008)	.002 (0.000)
	Between-group	.005 (.001)	.005 (.001)	0.000 (0.000)
WfH-workers	Overall	.252 (.045)	.218 (.027)	-.034 (.001)
	Between-group	.019 (.008)	.008 (.003)	-.011 (0.000)

**Note:** Table 8 displays Theil indices, bootstrapped standard errors, stratified across stock owner groups, weighted by survey weights. "Overall" related to Equation 4 and "Between-group" refers to income inequality between the groups of stock owners and those who do not own stocks, which is computed by the second sum of Equation 4.

groups, potentially leading to higher asset returns also for lower-income groups in the future.

## 5 Robustness

We check the robustness of earlier results in eleven directions: (i) We show that the increase in SMP in Germany continues beyond 2020;(ii) that the increase in WfH and SMP during the Covid-19-period is not specific to Germany but can be also observed in many other European countries; (iii) that the outcome variable, i.e. SMP of working household heads, is usefully defined; (iv) that results also hold when we run Probit instead of OLS regressions; (v) that WfH contributes to explaining SMP also in earlier years; (vi) that our main results hold when we consider additional potential determinants of SMP; (vii) that the result is not driven by the entrance of neobrokers into the German retail market; (viii) that main results hold when we use a fixed panel of individuals; (ix) that results on the different impact of WfH for various income groups also holds in IV-regressions; (x) that the distributional analysis built on income groups largely holds when we use education as indicator of socio-economic status; and (xi) that main results hold when we use gross instead of net wealth.

- (i) **SMP-increase beyond 2020.** At the time of our analysis, SOEP data are available only until 2020. To address concerns that the comovement of WfH and SMP between 2019 and 2020 may be driven by a time-specific unobserved event, we use additional data to assess whether the relationship persists. The German “Aktieninstitut” (translated as the Institute for Stock Markets) conducts an annual survey of the German adult population, with results available through 2023 (these data are not publicly available). This survey asks whether individuals hold stocks. Figure B.1 plots the respective SMP shares from this survey and the SOEP survey (as shown in Figure 1). Both datasets exhibit similar trends: SMP declines from 2001 onwards, stabilizes during the 2010s, increases from 2016, jumps in 2020, and remains elevated or increases further in the Aktieninstitut survey. However, the SMP levels in the Aktieninstitut survey are much lower—nearly half—because of three reasons: first, it includes youth, retirees, and non-working individuals (which are less likely to hold stocks), it uses a somewhat narrower definition of stock holdings (excluding risky assets like bonds and crypto),

and it does not consider stock holdings of other household members. This also explains why the 2020 SMP increase is smaller in the Aktieninstitut data (about 15%), as WfH is primarily relevant for working individuals, a subset of the adult population.

- (ii) **Our case is not specific to Germany.** A potential concern is that a country-specific unobserved factor drives the observed relationship. To address this, we analyze SMP in other European countries using the HFCS survey, a project of household surveys coordinated by the European Central Bank. The HFCS data, collected in 2017 and 2021, span the years 2019–2020. Figure B.2 shows the change in WfH and SMP across 20 European countries. Germany exhibits relatively strong increases in both dimensions, and we claim that only about one third of the SMP-increase may be caused by WfH. However, it seems reassuring that the increase aligns with a broader European pattern, as indicated by the regression line. This is further supported by Figure B.3, which displays WfH and SMP levels for 2017 and 2020, confirming a positive relationship. Unfortunately, the HFCS survey lacks sufficient individual-level detail to replicate our German analysis.
- (iii) **Modifications of SMP variable.** In our main analysis, SMP is based on an SOEP item asking whether the respondent or another household member owned risky assets (e.g., stocks, funds, bonds, or equity options) in the previous calendar year. To analyze this at the individual level, we attribute ownership to household heads, assuming respondents know their own portfolios better than those of other household members. A complementary study, SOEP-COV, provides individual-level data on risky asset ownership for a subset of SOEP participants, tailored to the Covid-19 pandemic. Despite its small sample size (2,651 observations for our main specification), Table B.1 shows that 81% of respondents in both studies report consistent ownership information. The remaining 19% could reflect timing differences (SOEP is retrospective; SOEP-COV captures current ownership) or slight differences in question wording. Despite these discrepancies, the high overlap supports the reliability of our data.

- (iv) **Probit models.** While OLS is straightforward and interpretable, it can produce predicted probabilities exceeding 100%. To address this, we replicate our analysis using a Probit model, frequently used in SMP studies (e.g., Bogan, 2008; Grinblatt et al., 2012). Table B.2 in the Appendix shows that Probit and Probit IV results are consistent with OLS findings in terms of coefficient signs and significance.
- (v) **WfH as SMP-determinant before 2020.** Concerns may arise that WfH’s role in SMP is unique to 2020. While WfH is unlikely to match the importance of wealth, income, or education as an SMP determinant, its relevance before 2020 provides reassurance. Using data from 2012–2014 (as WfH was not surveyed from 2015–2019), Table B.3 in the Appendix replicates our main specification, with some minor omissions due to data limitations. Results suggest a stable and positive relationship between WfH and SMP prior to 2020: Coefficients roughly predict 2.3-3.6 pp higher SMP for WfH-individuals. The coefficient for 2012 is not significant, the one for 2013 is significant at 10% and the one for 2014 is significant at 5%.
- (vi) **Considering further SMP-determinants.** Our main specification builds on Hong et al. (2004), which we replicate in Table B.4, column (1) in the Appendix for convenience. However, additional variables could influence SMP, so we account for four that have been discussed in the literature. First, the use of online banking is a potentially omitted variable, as it could intuitively be related to both working from home and stock market participation. The coefficient for online banking is quite large but not significant, while the coefficient for WfH remains robust to the inclusion of online banking, as shown in column (2). Second, political preferences have been identified as another determinant of SMP, with left-wing voters being less likely to own stocks (Kaustia and Torstila, 2011). We include a variable measuring political orientation on a scale from 0 (left) to 10 (right). In line with the literature, the coefficient for political orientation is significant in column (3) and indicates that a shift across the entire political spectrum from left to right increases the likelihood of entering the stock market by 5 percentage

points. The coefficient for WfH remains unaffected. Third, we add church attendance as a measure of sociability or religiosity, following the argument by Hong et al. (2004). The coefficient for WfH remains unchanged, and the control variable for church attendance is insignificant (column 4), likely because church attendance is less common in Germany than in the United States. Fourth, health is considered a determinant that may extend the horizon of decision-making and increase the willingness to invest in stocks. Column (5) shows that health, measured by the physical component score (a general health measure from the SOEP), has a positive and significant association with SMP, while the coefficient for WfH remains unaffected. Column (6) shows an insignificant relationship between children in the household and SMP, leaving the coefficient of interested unaffected.

**(vii) Customers of neobrokers.** The years around 2020 witnessed the market entry and rise of neobrokers in Germany. These brokers attract customers with very low trading costs, contributing to a rise in SMP. While no national statistics on neobroker customers are available, Trade Republic, a leading neobroker, published a study providing information about the age and income of its customers (Kritikos et al., 2022). According to the study, 70% of its customers are younger than 35 years, and 30% belong to the lower half of the income distribution. By contrast, the corresponding figures for “new stock owners” in our study are 19% and 44%, respectively (see Table 2). While the income figures are relatively similar, the neobroker customers’ age group is almost entirely distinct from the representative sample of working household heads analyzed in this study. Consequently, our results do not appear to be driven by neobroker customers.

**(viii) Fixed panel of individuals.** To address concerns that differences in sample size across specifications might affect comparability, we rerun the main regressions from Table 3 using a fixed panel of individuals (Table B.5 in the Appendix). The results are remarkably similar to the original findings, indicating that changes in sample size due to variable availability are not driving the results.

- (ix) **IV-regressions for income groups.** We replicate the regressions in Table 7, analyzing the effect of WfH on SMP for individuals in the lower 25%, middle 50%, and upper 25% of the income distribution, using the IV approach. As shown in Table B.6 in the Appendix, the IV results confirm the OLS findings.
- (x) **Education as indicator of socio-economic status.** Above, we demonstrated that the effect of WfH on stock market entry is driven by lower-income groups, with no effect for the top 25% of income earners. To test whether this relationship holds for other dimensions of socioeconomic status, we divide the sample by educational background into primary, secondary, and tertiary education. The majority of our sample has at least a secondary degree (61%) or tertiary degree (32%). Results in Table B.7 in the Appendix indicate that the effect is driven by individuals with a secondary degree, with a point estimate of 0.025 that is significant at the 5% level (column 2). The coefficients for the other two educational groups are insignificant (columns 1 and 3). While the primary education group is too small to yield reliable estimates, the insignificant result for tertiary-educated individuals suggests no effect for the most highly educated. The same pattern holds in the IV estimation. This educational split indicates that our findings are driven by two overlapping groups with similar socioeconomic status: lower-income earners and individuals without higher education.
- (xi) **Using gross wealth instead of net wealth.** To address outliers and skewness in the wealth distribution, we log-transform the wealth variable, adding a marginal unit for zero wealth to avoid undefined values. However, this approach excludes individuals with negative net wealth. To ensure that our results are not biased by this exclusion, we replicate the analysis using gross wealth, which allows us to retain the full sample, increasing it by approximately 7%. Table B.8 presents the results using gross wealth with the same sample as the main specification, while Table B.9 includes gross wealth with the extended sample, capturing individuals with negative net wealth. The coefficients of interest remain robust across both wealth measures and sample com-

positions, confirming that our findings are not influenced by the log transformation's sample adjustment.

## 6 Conclusion

The persistently limited degree of stock market participation (SMP) across nearly all countries is a concern for policymakers, as it contributes to a more unequal society. Over the long term, stock returns are systematically higher than those of other assets, such as bank deposits. Yet, large segments of the population who are reasonably capable of holding stocks choose not to do so. Since this reluctance is often associated with lower income and other dimensions of lower socioeconomic status, the lack of SMP exacerbates societal inequality.

Addressing this issue is challenging for policymakers, as it involves deep-rooted financial behaviors and constraints. Against this backdrop, the Covid-19 pandemic presents an interesting case: the enforcement of WfH led to a significant increase in SMP among working household heads, in combination with other pandemic-induced changes. WfH allows working individuals to save commuting time and provides greater flexibility in allocating time between work and leisure. This relaxation of time constraints introduces a novel way of reducing the participation costs of SMP.

This research also breaks new ground by analyzing the potential distributional effects of the increase in SMP. While the literature has generally overlooked the relationship between SMP and inequality, our findings show that new entrants to the stock market have indeed broadened the base of stock ownership, particularly among middle-income groups. Notably, the effect of WfH is even more pronounced in this regard, as it disproportionately benefits middle- and lower-income groups by increasing their SMP.

These findings highlight the need for further exploration of the distributional effects of other SMP determinants and whether policy interventions could mitigate barriers to stock market participation, especially for disadvantaged groups. Understanding these dynamics

could help design policies that not only increase SMP but also promote financial inclusion and reduce inequality.

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# ONLINE APPENDIX

to

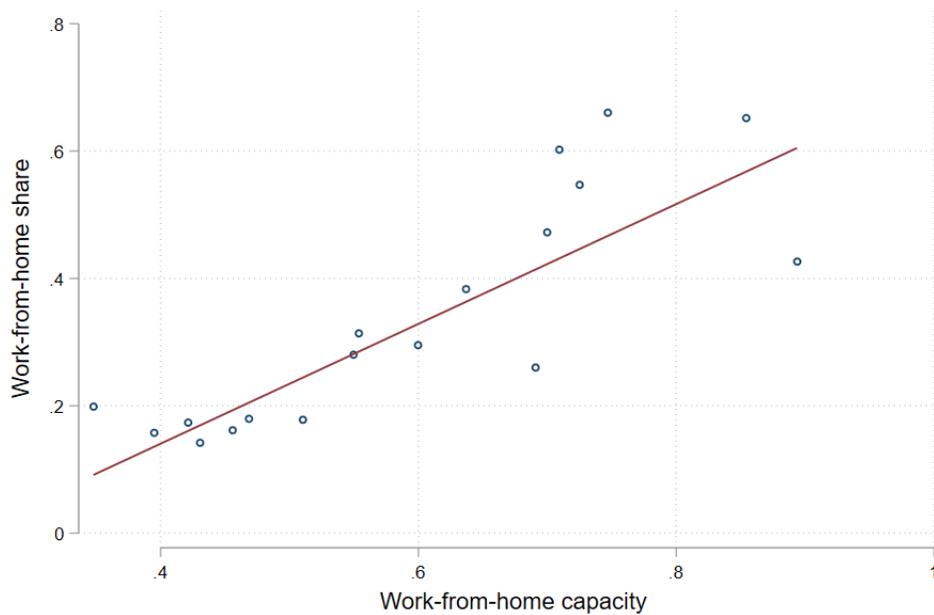
Stock Market Participation, Work from Home, and Inequality

## A Appendix

Table A.1: Description of variables

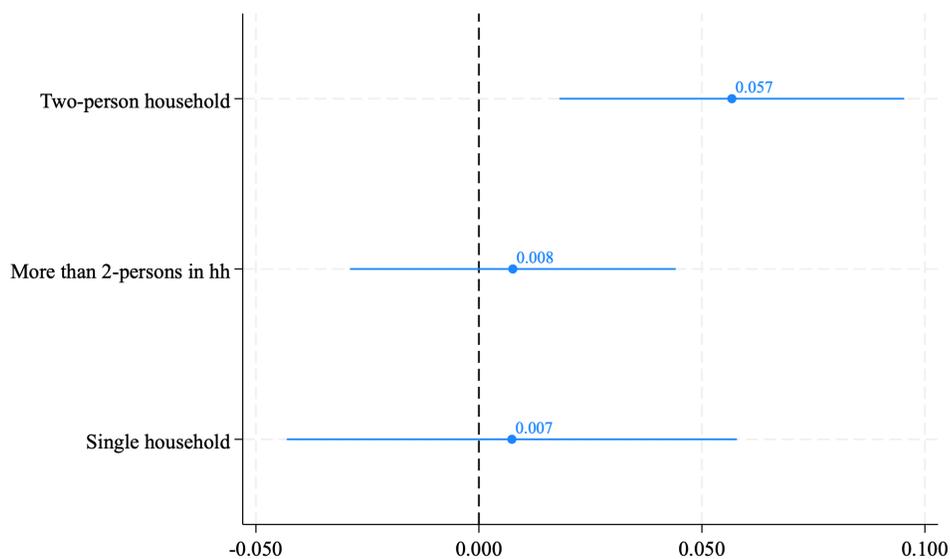
<b>Variable</b>	<b>Description</b>
SMP	This variable is equal to one if the household head reports that someone in the household owns risky assets, and zero otherwise.
WfH	This variable is one if the respondent indicates that they work from home, and zero otherwise.
Net overall wealth	Assets minus liabilities.
Household income	Disposable household income, adjusted to household size by OECD-equivalent scale.
Years of education	The number of years individuals were in school or university.
Age	Individuals' age in 2020.
Female	Equals one if respondent is female, and zero otherwise.
Married	Equals one if respondent is married, and zero otherwise.
Urban	Equals one if BIK region has at least 100k inhabitants and zero otherwise. BIK regions are a widely used classification, used by administrative authorities.
Migration background	Equals one if at least one parent or respondent themselves was born abroad, and zero otherwise.
Risk tolerance	Based on Likert-scale that elicits willingness to take risks from 0 to 10. Dummy is equal to one if risk tolerance is 6 and above, and zero otherwise.
Sociability	Equals one if number of close friends is 4 or higher, and zero otherwise.
Optimism	Equals one if respondent is rather optimistic, and zero if respondent is rather pessimistic.
Openness	Equals one if respondent is rather open, and zero if respondent is rather not open.

Figure A.1: First stage binned scatterplots



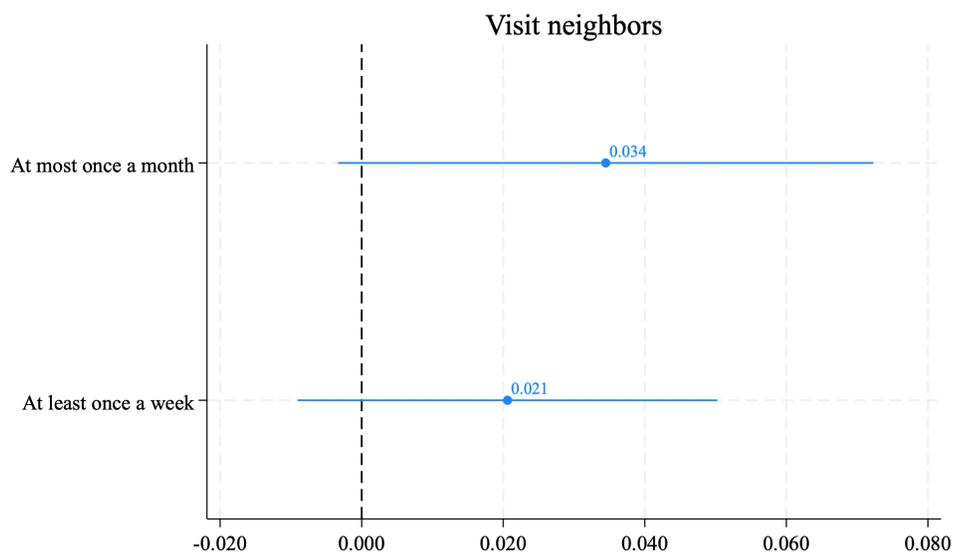
**Notes:** The binscatter depicts the first stage for remote work and the instruments. The plot shows a positive relationship between the work-from-home (WfH) capacity and the share of remote work, whereby bins are formed based on some capacity ranges. The WfH-capacity measures the pre-pandemic share of individuals in a NACE industry, who could work from home, assuming the employer allows it. The positive relationship is intuitive, as the capacity to work from home should be related to actually working from home. Source: Own computations based on SOEPv37.

Figure A.2: Coefficients by household size



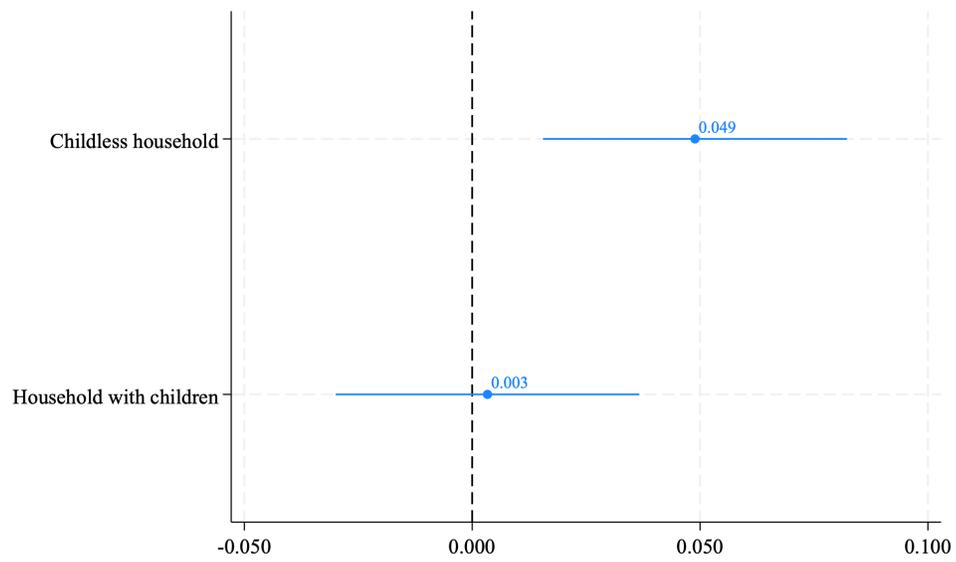
The plot shows coefficients of interest from estimating Equation 1, for households of various sizes.

Figure A.3: Coefficients by sociability



The plot shows coefficients of interest from estimating Equation 1, for the sample of individuals who visit their neighbors at least once a week and those of most once a month.

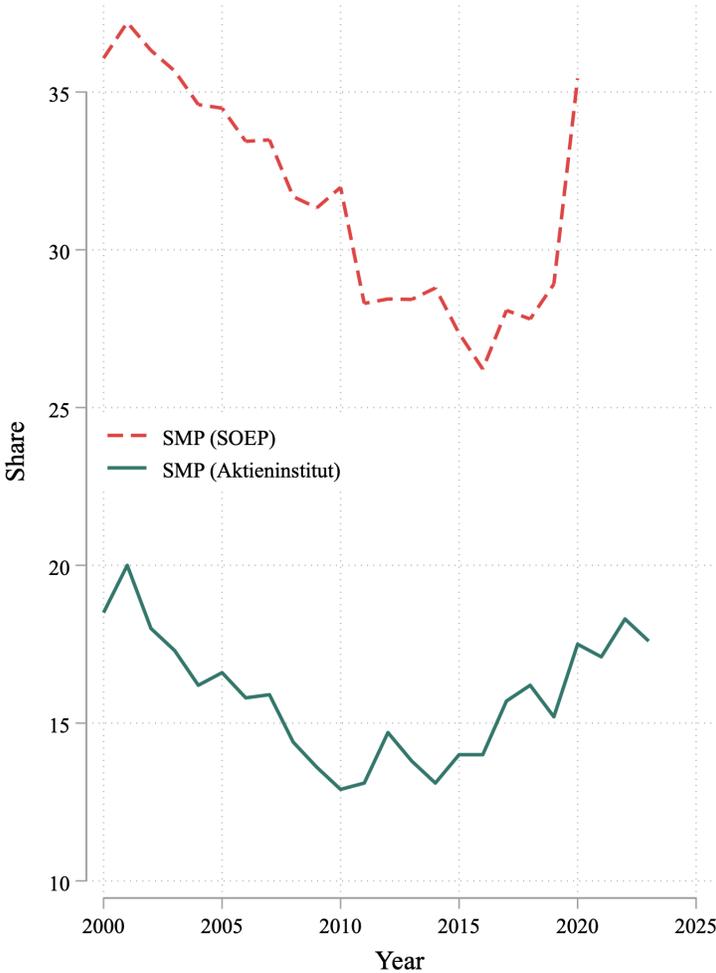
Figure A.4: Coefficient by households with and without children



The plot shows coefficients of interest from estimating Equation 1, for households with and without children.

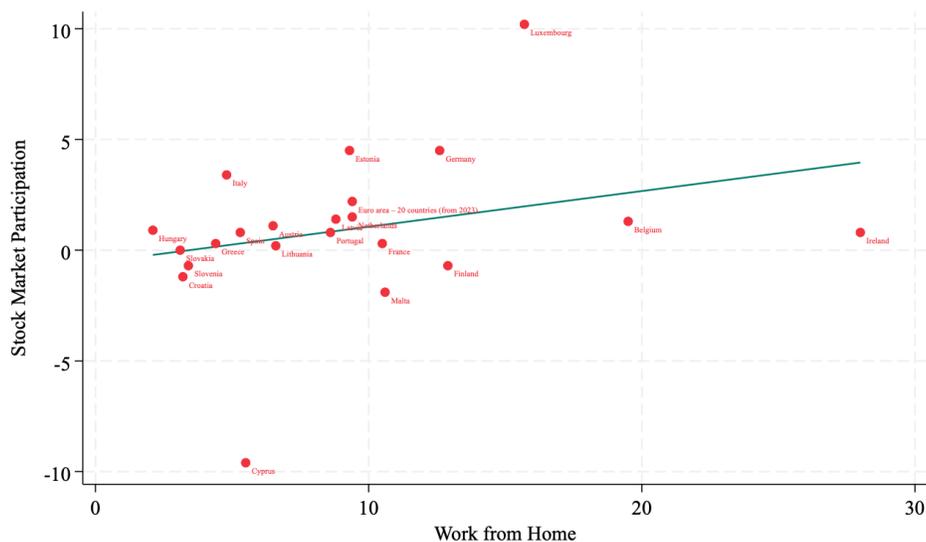
# B Appendix

Figure B.1: SMP Timeseries



**Notes:** The plot shows time series for SMP. The red dashed line is based on SOEP data and indicates the SMP among working household heads. The green line is based on data from Deutsches Aktieninstitut and indicates the SMP among the whole German population aged 16 or older.

Figure B.2: Changes in shares of WfH and SMP across EU countries



**Notes:** The plot shows a positive association between changes in the WfH-share and SMP from 2017 to 2021 (in percentage points) across EU-countries. Sources: HFCS, ECB, and Eurostat.

Table B.1: Cross-tabulations

		SOEP-COV (individual)		
		No risky assets	Risky assets	Total
SOEP-CORE (household)	No risky assets	57.18	5.52	62.7
	Risky assets	10.89	26.42	37.3
	Total	68.07	31.93	100

**Notes:** The table shows, how risky asset ownership (“stock market participation”), varies across the main SOEP study, where stock ownership is measured on the household level and then attributed to the respondent only and the SOEP-COV study, where stock ownership is measured on the individual level. The table depicts large overlap of stock ownership, indicating that the measure on the household level approximates individual stock ownership well enough.



Table B.2: Probit estimations

VARIABLES	Main Results with Probit			
	(1) Probit SMP	(2) Probit SMP	(3) Probit SMP	(4) Pr. IV SMP
Work from home		0.182*** (0.041)	0.093** (0.047)	0.528** (0.207)
SMP (first lag)			1.780*** (0.045)	1.730*** (0.062)
Log net wealth	0.090*** (0.008)	0.085*** (0.009)	0.040*** (0.009)	0.034*** (0.009)
Log disposable hh income	0.439*** (0.041)	0.408*** (0.043)	0.263*** (0.049)	0.201*** (0.053)
Secondary education	0.217 (0.337)	0.312 (0.368)	0.029 (0.355)	-0.016 (0.375)
Tertiary education	0.411 (0.338)	0.475 (0.369)	0.136 (0.357)	-0.015 (0.381)
Age	-0.012*** (0.002)	-0.012*** (0.002)	-0.010*** (0.002)	-0.009*** (0.002)
Female	-0.088** (0.037)	-0.076** (0.038)	-0.080* (0.044)	-0.058 (0.046)
Married	0.008 (0.039)	0.000 (0.040)	-0.004 (0.046)	-0.012 (0.046)
Urban	0.146*** (0.040)	0.139*** (0.042)	0.074 (0.048)	0.046 (0.051)
Migration background	-0.376*** (0.050)	-0.374*** (0.052)	-0.278*** (0.061)	-0.227*** (0.063)
Risk tolerance	0.059 (0.036)	0.057 (0.038)	0.019 (0.044)	0.010 (0.044)
Sociability	0.068* (0.036)	0.052 (0.037)	0.066 (0.043)	0.054 (0.043)
Optimism	0.128** (0.050)	0.150*** (0.052)	0.095 (0.061)	0.097 (0.059)
Openness	-0.081** (0.036)	-0.101*** (0.038)	-0.004 (0.043)	-0.035 (0.045)
State FE	yes	yes	yes	yes
Constant	-5.765*** (0.516)	-5.523*** (0.548)	-3.883*** (0.574)	-3.251*** (0.626)
Observations	5,797	5,377	5,307	5,209
Pseudo R-squared	0.127	0.126	0.371	–

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

**Notes:** The table shows the replication of the main results from Table 3, using Probit instead of OLS and Probit-IV instead of IV. A Probit model is commonly used for binary outcomes, such as stock market participation, while we decided to use OLS in the main specification as it allows for a more intuitive interpretation of coefficients. The coefficients' direction and significance are highly similar to the linear model.

Table B.3: Years prior to 2020

	(1)	(2)	(3)
VARIABLES	2012 SMP	2013 SMP	2014 SMP
Work from home	0.023 (0.015)	0.026* (0.015)	0.036** (0.016)
Log net wealth	0.020*** (0.001)	0.021*** (0.001)	0.022*** (0.001)
Log disposable hh income	0.172*** (0.018)	0.128*** (0.015)	0.121*** (0.015)
Secondary education	0.028 (0.035)	0.030 (0.040)	0.029 (0.047)
Tertiary education	0.132*** (0.037)	0.147*** (0.042)	0.140*** (0.048)
Age	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)
Female	-0.017 (0.012)	-0.005 (0.012)	-0.002 (0.013)
Married	0.006 (0.012)	0.007 (0.013)	-0.005 (0.013)
Urban	0.032** (0.012)	0.036*** (0.013)	0.047*** (0.013)
Migration background	-0.093*** (0.015)	-0.101*** (0.016)	-0.091*** (0.018)
Risk tolerance	0.020* (0.011)	0.014 (0.012)	0.006 (0.013)
State FE	yes	yes	yes
Constant	-1.631*** (0.174)	-1.222*** (0.148)	-1.180*** (0.150)
Observations	5,961	5,615	5,027
R-squared	0.161	0.140	0.137

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

**Notes:** The table shows the results for estimating the main specification from Table 3, column (2) for years prior to 2020. The coefficients indicate that the positive association between remote work and stock market participation holds and is significant for most years prior to the COVID-19 pandemic, that imposed a shock on remote work. Due to missing observations in these years, we cannot include all controls that are part of the main estimation for 2020, i.e. sociability, optimism, and openness.

Table B.4: Adding more control variables

VARIABLES	Main Results with more controls					
	(1)	(2)	(3)	(4)	(5)	(6)
	M1 SMP	M2 SMP	M3 SMP	M4 SMP	M5 SMP	M6 SMP
Work from home	0.025** (0.012)	0.026** (0.013)	0.024** (0.012)	0.024** (0.012)	0.024** (0.012)	0.027** (0.012)
SMP (lag)	0.609*** (0.012)	0.618*** (0.014)	0.609*** (0.013)	0.608*** (0.012)	0.608*** (0.013)	0.611*** (0.013)
Log wealth	0.008*** (0.002)	0.008*** (0.002)	0.008*** (0.002)	0.008*** (0.002)	0.008*** (0.002)	0.008*** (0.002)
Log Disposable HH Income	0.063*** (0.011)	0.061*** (0.013)	0.064*** (0.011)	0.064*** (0.011)	0.060*** (0.011)	0.062*** (0.011)
Secondary education	-0.017 (0.047)	-0.033 (0.049)	-0.024 (0.052)	-0.018 (0.047)	-0.029 (0.050)	-0.023 (0.052)
Tertiary education	0.011 (0.048)	-0.008 (0.050)	0.007 (0.053)	0.009 (0.048)	-0.003 (0.051)	0.009 (0.052)
Age	-0.002*** (0.000)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.000)	-0.002*** (0.001)	-0.002*** (0.001)
Female	-0.021* (0.011)	-0.017 (0.011)	-0.017 (0.011)	-0.020* (0.011)	-0.019* (0.011)	-0.019* (0.011)
Married	0.000 (0.011)	-0.002 (0.012)	-0.001 (0.011)	-0.001 (0.011)	0.001 (0.011)	0.009 (0.012)
Rurality	0.019* (0.011)	0.018 (0.012)	0.019 (0.012)	0.020* (0.011)	0.017 (0.011)	0.015 (0.011)
Migration background	-0.065*** (0.014)	-0.071*** (0.014)	-0.064*** (0.014)	-0.065*** (0.014)	-0.064*** (0.014)	-0.065*** (0.014)
Risk tolerance	0.005 (0.010)	0.001 (0.011)	0.003 (0.011)	0.006 (0.011)	0.005 (0.011)	0.001 (0.011)
Sociability	0.016 (0.010)	0.017 (0.011)	0.013 (0.010)	0.015 (0.010)	0.015 (0.010)	0.010 (0.010)
Optimism	0.023* (0.014)	0.007 (0.015)	0.024* (0.014)	0.022 (0.014)	0.020 (0.014)	0.025* (0.014)
Openness	-0.004 (0.010)	-0.010 (0.011)	-0.006 (0.010)	-0.005 (0.010)	-0.005 (0.010)	-0.004 (0.010)
State FE	yes	yes	yes	yes	yes	yes
Online banking		0.010 (0.012)				
Political orientation			0.004 (0.003)			
Church attendance				0.022 (0.014)		
Health					0.002*** (0.001)	
Children in HH						-0.017 (0.011)
Constant	-0.485*** (0.111)	-0.429*** (0.133)	-0.508*** (0.115)	-0.489*** (0.111)	-0.559*** (0.116)	-0.462*** (0.116)
Observations	5,306	4,417	5,155	5,291	5,245	5,208
R-squared	0.454	0.459	0.453	0.454	0.455	0.459

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Notes:** The table shows the results for adding more control variables. Column (1) denotes the baseline and is the same as column (3) of Table 3. Column (2) adds the use of online banking, column (3) adds political orientation (left vs. right), column (4) adds church attendance, and column (5) adds health, as measured by a general physical health score that consists of various components. Overall, the coefficient of interest stays very robust to the inclusion of the additional controls.

Table B.5: Main regressions with fixed sample

VARIABLES	Main Results			
	(1)	(2)	(3)	(4)
	OLS SMP	OLS SMP	OLS SMP	IV SMP
Work from home		0.067*** (0.015)	0.027** (0.012)	0.127** (0.053)
SMP (first lag)			0.612*** (0.013)	0.605*** (0.012)
Log net wealth	0.024*** (0.002)	0.023*** (0.002)	0.008*** (0.002)	0.007*** (0.002)
Log disposable hh income	0.150*** (0.013)	0.141*** (0.013)	0.062*** (0.011)	0.049*** (0.012)
Secondary education	-0.002 (0.052)	-0.005 (0.052)	-0.021 (0.050)	-0.024 (0.071)
Tertiary education	0.077 (0.053)	0.058 (0.053)	0.007 (0.051)	-0.021 (0.073)
Age	-0.004*** (0.001)	-0.004*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)
Female	-0.033** (0.013)	-0.029** (0.013)	-0.022** (0.011)	-0.016 (0.011)
Married	0.004 (0.014)	0.003 (0.014)	-0.000 (0.011)	-0.002 (0.011)
Urban	0.057*** (0.014)	0.052*** (0.014)	0.021* (0.011)	0.013 (0.012)
Migration background	-0.128*** (0.017)	-0.123*** (0.017)	-0.061*** (0.014)	-0.054*** (0.014)
Risk tolerance	0.026** (0.013)	0.024* (0.013)	0.004 (0.011)	0.003 (0.011)
Sociability	0.019 (0.013)	0.017 (0.013)	0.016 (0.010)	0.013 (0.010)
Optimism	0.049*** (0.017)	0.049*** (0.017)	0.023* (0.014)	0.024* (0.014)
Openness	-0.038*** (0.013)	-0.042*** (0.013)	-0.005 (0.010)	-0.011 (0.011)
State FE	yes	yes	yes	yes
Constant	-1.334*** (0.134)	-1.251*** (0.134)	-0.468*** (0.113)	-0.353*** (0.133)
Observations	5,209	5,209	5,209	5,209
R-squared	0.149	0.152	0.456	0.448

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

**Notes:** While the main output in Table 3 is based on a sample that is shrinking with the inclusion of more variables (due to missing values), we re-run the same regression using a fixed sample of 6,715 observations in a complete case analysis. The coefficients are highly similar, indicating that the sample composition does not cause any bias to our analysis.

Table B.6: Split sample on income groups, using the IV specification

Instrumental Variables Results			
	(1)	(2)	(3)
VARIABLES	Bottom25 SMP	Middle50 SMP	Top25 SMP
Work from home	0.120 (0.103)	0.148 (0.090)	0.069 (0.094)
SMP (first lag)	0.617*** (0.041)	0.614*** (0.016)	0.586*** (0.023)
Log net wealth	0.006*** (0.002)	0.007** (0.003)	0.001 (0.006)
Log disposable hh income	-0.021 (0.020)	0.048 (0.034)	0.045* (0.026)
Secondary education	0.013 (0.048)	-0.046 (0.105)	-0.000 (0.030)
Tertiary education	0.002 (0.055)	-0.047 (0.109)	
Age	-0.001 (0.001)	-0.002*** (0.001)	-0.002 (0.001)
Female	-0.028 (0.018)	-0.010 (0.012)	-0.032 (0.023)
Married	-0.028 (0.023)	-0.011 (0.017)	0.033 (0.024)
Urban	-0.020 (0.025)	0.020 (0.019)	0.018 (0.024)
Migration background	-0.009 (0.023)	-0.057*** (0.019)	-0.084** (0.038)
Risk tolerance	0.006 (0.025)	-0.007 (0.014)	0.021 (0.022)
Sociability	0.013 (0.024)	0.003 (0.014)	0.029 (0.019)
Optimism	0.007 (0.027)	0.013 (0.023)	0.054* (0.029)
Openness	0.008 (0.021)	-0.011 (0.016)	-0.015 (0.020)
State FE	yes	yes	yes
Constant	0.278 (0.177)	-0.266 (0.360)	-0.313 (0.254)
Observations	852	2,862	1,495
R-squared	0.374	0.405	0.401

Standard errors in parentheses  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Notes:** Extending Table 7 and contributing to the distributional analysis, this table shows the results for estimating our instrumental variables specification for the subsamples of the lowest 25%, middle 50%, and top 25% of the income distribution, respectively. Confirming the OLS findings, the effect is only positive and significant for the lowest income group.

Table B.7: Effect sizes for individuals of various educational backgrounds

VARIABLES	Main Results					
	(1) primary SMP	(2) secondary SMP	(3) tertiary SMP	(4) primaryIV SMP	(5) secondaryIV SMP	(6) tertiaryIV SMP
Work from home	-0.040 (0.265)	0.016 (0.017)	0.028* (0.017)	4.447 (4.290)	0.111 (0.077)	0.118 (0.088)
SMP (first lag)		0.628*** (0.018)	0.589*** (0.018)		0.626*** (0.017)	0.586*** (0.016)
Log net wealth	-0.047 (0.047)	0.007*** (0.002)	0.008** (0.003)	-0.065* (0.036)	0.006*** (0.002)	0.007** (0.003)
Log disposable hh income	-0.146 (0.225)	0.079*** (0.017)	0.054*** (0.014)	0.515 (0.503)	0.061*** (0.020)	0.045*** (0.016)
Age	0.006 (0.011)	-0.002*** (0.001)	-0.003*** (0.001)	-0.050 (0.046)	-0.002** (0.001)	-0.003*** (0.001)
Female	-0.128 (0.228)	-0.005 (0.014)	-0.043** (0.017)	0.209 (0.305)	0.000 (0.012)	-0.041*** (0.016)
Married	0.366* (0.176)	-0.012 (0.014)	0.013 (0.017)	0.888* (0.463)	-0.009 (0.012)	0.006 (0.017)
Urban	-0.329* (0.138)	0.011 (0.014)	0.033* (0.019)	-0.357 (0.338)	0.011 (0.016)	0.022 (0.020)
Migration background	-0.196 (0.242)	-0.037** (0.017)	-0.091*** (0.023)	0.004 (0.315)	-0.030* (0.016)	-0.077*** (0.021)
Risk tolerance	0.195 (0.236)	0.007 (0.014)	0.001 (0.016)	0.739* (0.449)	0.004 (0.015)	-0.000 (0.016)
Sociability	0.250 (0.167)	0.017 (0.013)	0.010 (0.016)	0.558* (0.314)	0.018 (0.012)	0.003 (0.013)
Optimism	-0.235 (0.193)	0.020 (0.017)	0.028 (0.024)	-0.494 (0.311)	0.020 (0.014)	0.030 (0.024)
Openness	0.350 (0.482)	0.002 (0.013)	-0.012 (0.016)	-0.831 (0.938)	-0.006 (0.015)	-0.017 (0.020)
State FE	yes	yes	yes	yes	yes	yes
Constant	1.775 (1.859)	-0.664*** (0.159)	-0.385*** (0.145)	-2.028 (2.911)	-0.494** (0.196)	-0.321** (0.142)
Observations	29	2,901	2,377	27	2,844	2,338
R-squared	0.833	0.440	0.430		0.437	0.426

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Notes:** In this table, we show the results of a split-sample analysis regarding different levels of education. While the lowest educational group is too small (45 and 39 observations) to yield any meaningful coefficients, the table shows that the effect is only significant for individuals with a secondary education, and not for individuals with tertiary (higher) education. This result is in line with the one on various income groups.

Table B.8: Main results, using gross wealth and fixed sample

VARIABLES	(1) OLS SMP	(2) OLS SMP	(3) OLS SMP	(4) IV SMP
Work from home		0.071*** (0.015)	0.025** (0.012)	0.129** (0.064)
SMP (first lag)			0.611*** (0.012)	0.607*** (0.011)
Log gross wealth	0.022*** (0.002)	0.021*** (0.002)	0.007*** (0.002)	0.005*** (0.002)
Log disposable hh income	0.152*** (0.012)	0.141*** (0.013)	0.065*** (0.011)	0.051*** (0.016)
Secondary education	0.006 (0.053)	0.001 (0.049)	-0.016 (0.047)	-0.023 (0.048)
Tertiary education	0.084 (0.054)	0.066 (0.050)	0.013 (0.048)	-0.019 (0.052)
Age	-0.003*** (0.001)	-0.003*** (0.001)	-0.002*** (0.000)	-0.002*** (0.001)
Female	-0.035*** (0.012)	-0.031** (0.013)	-0.021** (0.011)	-0.017** (0.008)
Married	0.005 (0.013)	0.002 (0.014)	0.000 (0.011)	-0.001 (0.010)
Urban	0.052*** (0.014)	0.049*** (0.014)	0.019* (0.011)	0.013 (0.014)
Migration background	-0.126*** (0.015)	-0.126*** (0.016)	-0.066*** (0.014)	-0.055*** (0.012)
Risk tolerance	0.023* (0.012)	0.023* (0.013)	0.004 (0.010)	0.002 (0.010)
Sociability	0.024** (0.012)	0.018 (0.013)	0.016 (0.010)	0.013 (0.009)
Optimism	0.045*** (0.016)	0.051*** (0.017)	0.023* (0.014)	0.024* (0.013)
Openness	-0.032*** (0.012)	-0.040*** (0.013)	-0.004 (0.010)	-0.011 (0.011)
State FE	yes	yes	yes	yes
Constant	-1.375*** (0.126)	-1.266*** (0.130)	-0.500*** (0.111)	-0.365** (0.152)
Observations	5,797	5,377	5,307	5,209
R-squared	0.149	0.149	0.454	0.447

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

**Notes:** The table shows regression results for estimating the main specification from Section 2.3., with log gross wealth instead of log net wealth. Column (1) depicts the results of an OLS estimation of stock market participation in 2020 on various individual characteristics. Column (2) adds WfH as an explanatory variable. Column (3) adds stock ownership in 2019, such that other coefficients can be interpreted with respect to entrants between 2019 and 2020. Finally, column (4) shows the coefficients for a 2-stage-least-squares instrumental variables estimation, whereby WfH is instrumented by WfH-capacity, an indicator at the NACE industry level – at which standard errors are clustered in this specification.

Table B.9: Main results, using gross wealth

VARIABLES	(1) OLS SMP	(2) OLS SMP	(3) OLS SMP	(4) IV SMP
Work from home		0.068*** (0.014)	0.023** (0.011)	0.112** (0.056)
SMP (first lag)			0.611*** (0.012)	0.608*** (0.011)
Log gross wealth	0.023*** (0.002)	0.023*** (0.002)	0.008*** (0.001)	0.007*** (0.002)
Log disposable hh income	0.149*** (0.012)	0.139*** (0.012)	0.064*** (0.010)	0.052*** (0.015)
Secondary education	0.014 (0.045)	0.010 (0.041)	-0.005 (0.039)	-0.009 (0.041)
Tertiary education	0.096** (0.046)	0.080* (0.043)	0.026 (0.040)	0.000 (0.046)
Age	-0.003*** (0.001)	-0.003*** (0.001)	-0.002*** (0.000)	-0.002*** (0.001)
Female	-0.035*** (0.012)	-0.032*** (0.012)	-0.021** (0.010)	-0.017** (0.007)
Married	0.000 (0.012)	-0.003 (0.013)	-0.004 (0.010)	-0.006 (0.010)
Urban	0.051*** (0.013)	0.051*** (0.014)	0.022** (0.011)	0.016 (0.013)
Migration background	-0.122*** (0.014)	-0.121*** (0.015)	-0.063*** (0.013)	-0.053*** (0.011)
Risk tolerance	0.023* (0.012)	0.023* (0.012)	0.005 (0.010)	0.003 (0.009)
Sociability	0.025** (0.012)	0.020 (0.012)	0.016* (0.010)	0.014 (0.009)
Optimism	0.043*** (0.015)	0.048*** (0.016)	0.021 (0.013)	0.022* (0.013)
Openness	-0.029** (0.012)	-0.036*** (0.012)	-0.004 (0.010)	-0.010 (0.010)
State FE	yes	yes	yes	yes
Constant	-1.383*** (0.119)	-1.282*** (0.123)	-0.524*** (0.104)	-0.411*** (0.139)
Observations	6,228	5,769	5,686	5,582
R-squared	0.158	0.157	0.457	0.453

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

**Notes:** The table shows regression results for estimating the main specification from Section 2.3., with log gross wealth. Column (1) depicts the results of an OLS estimation of stock market participation in 2020 on various individual characteristics. Column (2) adds WfH as an explanatory variable. Column (3) adds stock ownership in 2019, such that other coefficients can be interpreted with respect to entrants between 2019 and 2020. Finally, column (4) shows the coefficients for a 2-stage-least-squares instrumental variables estimation, whereby WfH is instrumented by WfH-capacity, an indicator at the NACE industry level – at which standard errors are clustered in this specification.