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Jan Brůha and Hana Brůhová Foltýnová*

Abstract

The outbreak of the COVID-19 pandemic and the subsequent introduction of anti-pandemic measures led to a substantial drop in mobility, including travelling to work and shopping, and an increase in virtual activities, mainly working from home and online shopping. The question addressed in this paper is whether this change is permanent and, if so, to what extent. We use panel data collected in five waves from the Czech adult urban population during and shortly after the COVID-19 pandemic. The data document a substantial switch to online activities during the pandemic. This switch seems to be semi-permanent, i.e., expected to last even after the lifting of the anti-pandemic measures. The main determinants of working from home are job type, industry and education. The main determinants of online shopping are age and education. We conclude that the pandemic and the related measures accelerated the diffusion of online activities among the Czech population, mainly among younger and more educated individuals.

Abstrakt

Vypuknutí pandemie COVID-19 a následné zavedení protipandemických opatření vedlo k podstatnému poklesu mobility, včetně cestování do práce a nakupování, a nárůstu virtuálních aktivit, zejména práce z domova a online nakupování. Tento článek řeší otázku, zda a do jaké míry je tato změna trvalá. Využíváme panelová data o dospělé městské populaci ČR posbíraná v pěti vlnách během pandemie COVID-19 a krátce po ní. Data dokládají výrazný přesun k online aktivitám během pandemie. Tento přesun se zdá být částečně trvalý: lze očekávat, že bude trvat i po zrušení protipandemických opatření. Hlavními determinantami práce z domova jsou typ zaměstnání, odvětví a vzdělání. Hlavními determinantami online nakupování jsou věk a vzdělání. Dospěli jsme k závěru, že pandemie a související opatření urychlily šíření online aktivit mezi českou populací, zejména mezi mladšími a vzdělanějšími jedinci.

JEL Codes: O33, Q54, R41.

Keywords: Coronavirus pandemic, online shopping, travel behavior, working from home.

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1. Introduction

The outbreak of the COVID-19 pandemic represented a huge negative shock that affected virtually every area of modern society. The fear of the coronavirus together with anti-pandemic measures, which included many forms of voluntary or imposed social distancing, self-isolation, curfews and lockdowns, led to a drop in mobility and an increase in the importance of online activities. The interesting question is whether any of the changes in mobility will be permanent and, if so, to what extent. As argued by Kirk and Rifkin (2020), times of crisis often bring about major transformations in society. Thus, will this unprecedented experience lead to permanent changes in the post-pandemic society?

During the pandemic, a large proportion of activities went virtual, amplifying pre-pandemic trends. Before the pandemic, the rate of regular (everyday) telecommuting was low, albeit increasing slowly (Shabanpour et al., 2018; Vilhelmson and Thulin, 2016). In Europe, including the Czech Republic, the number of workers who stated that they regularly worked from home increased from 4.6% to 5.2% between 2009 and 2019 (Eurostat, 2020). This share more than doubled to 12.3% in 2020 and reached 13.5% in 2021 (Eurostat, 2022a). An even higher increase was registered for hybrid (part-time) work from home (see Kogus et al., 2022 for evidence from Israel and the Czech Republic). Online shopping before the pandemic varied widely across countries, as well as across different product categories: age, education, income and experience all influenced uptake. In the Czech Republic, clothing, footwear, sporting goods and travel products were the most common items purchased online before the pandemic (OECD, 2018). Recent evidence indicates that there was an increase in the frequency of online shopping during the pandemic (Shen et al., 2022; Salon et al., 2021).

Will the uptake of modern technologies and the experience with online activities during the COVID-19 pandemic lead to permanent changes in behavior? This is an important and interesting question for policymakers in a wide range of areas from monetary policy to general economic policy to urban planning and mobility management. From the perspective of general economic policy, a shift towards online activities may make the economy more resilient to shocks similar to the COVID-19 pandemic. From the perspective of transport policy, a substantial increase in online shopping would influence city logistics. In addition, changes in the frequency of trips and possibly even destinations may influence traffic intensity and distribution.[1]

The trends in online activities are also relevant from the perspective of monetary policy. First, the increase in online shopping should be reflected in a change in inflation measurement. Second, it is well known (Cavallo, 2017) that inflation of online prices and inflation of goods sold in brick-and-mortar shops exhibit different dynamics (e.g., online prices are subject to more frequent changes, have lower mark-ups and cost factors pass through to them more quickly). Lower mark-ups and a faster pass-through of costs may lead to a change in Phillips curve parameters. Third, an increase in the adoption of ICT can affect productivity and therefore the equilibrium variables, such

[1] The increase in online activities will generally put further pressure on the demand for relevant infrastructure – not only good internet provision and IT applications and programs, but also good conditions for working from home, including legislation and sharing the costs of housing. If the move to a virtual environment were to continue, changes in schedules and in the type of activities, a decrease in office space demand, a decline in the number of brick-and-mortar stores and the supply of some new services may also have significant impacts on the structure and functioning of urban and rural areas and on transport in these areas.

as the equilibrium real interest rate. Fourth, an increase in working from home opportunities can make the labor market more flexible and matching more efficient. That would affect the business cycle properties of the labor market (Brown and Colton, 2023). For these reasons, it is vital that policymakers observe and evaluate trends in online activities.

In this paper, we present evidence that the pandemic has led to permanent changes in behavior due to experience with virtual activities during the pandemic. Using data from five waves of an online survey of Czech urban citizens, we concentrate on two regular activities: work and shopping. We ask whether the respondents expect to engage more in virtual activities after the pandemic and identify the characteristics of the respondents who expect to do so.

The rest of this paper is organized as follows. Chapter 2 presents a review of the literature, focusing on the factors influencing online work and shopping. Chapter 3 introduces the methodology and data and presents the basic statistics. Section 4 uses a nested logit model to identify the socio-demographic characteristics of the respondents related to their online activities. Section 5 applies an ordered probit model, which demonstrates a positive correlation between various online activities even after controlling for socio-demographic characteristics. The final chapter concludes this paper. The appendices contain additional material regarding transport behavior during and after the COVID-19 pandemic.

2. Literature Review

The development of the internet has allowed for the expansion of various online activities, a trend that was accelerated during the pandemic. This was natural as there was a significant decrease in physical trips due to the restrictive measures introduced to limit contact between individuals. In this part of the paper, we review the most important studies related to telecommuting and online shopping before, during and after the COVID-19 pandemic.

2.1 Telecommuting Potential

Elldér (2020) defines telework[2] as a concept related to working from home or other places rather than at the regular workplace. Thanks to the rise of information and communication technologies (ICT), people can substitute working at the workplace with teleworking. In recent years, ICT is no longer a barrier to teleworking (Aguilera et al., 2016). There are other factors that determine teleworking, such as the nature of the work, the support and culture of the organization, the home and family situation, and individual preferences and beliefs.

Even with high-quality ICT, not all jobs can be carried out remotely. Generally, the extent of telework seems to be highest in knowledge-intensive services, e.g., professional and ICT services, and lowest in manufacturing and less knowledge-intensive market services, including wholesale, retail and transportation (OECD, 2020). The COVID-19 pandemic revealed the working-from-

[2] In the Literature Review, we use the same terms used in the cited papers. Most of the literature, however, refers to home-based teleworking. In our analysis, we refer to work from home (WFH) to emphasise that the respondents analyzed in the survey worked from home. (However, teleworking is broader as it also includes work from places other than the workplace, not necessarily only from home; that said, it is usually associated with work using ICT).

home potential of various sectors. Dingel and Neiman (2020) estimate that 37% of jobs in the current US economy could be conducted entirely from home. This share, however, varies significantly across industries and incomes, with lower-income countries having a lower share of such positions. Similarly, Deng et al. (2020) find that about 39% of Canadian workers are in jobs that could plausibly be carried out from home. Most jobs in finance and insurance (85%), educational services (85%) and professional, scientific and technical services (84%) could be conducted remotely, while jobs in accommodation and food services (6%) and those in agriculture, forestry, fishing and hunting (4%) have almost no telework capacity.

Sociodemographic factors, such as gender, age, education, and number and age of children, influence the probability of working from home too. For studies conducted prior to the outbreak of the COVID-19 pandemic, there is a consensus that working from home is positively associated with a higher level of education and higher-income groups, being male and having children in the family (Turcotte, 2010; He and Hu, 2015). Sarbu (2015) found that having children under six and working overtime had a positive impact on working from home. They also found that women were more likely to work from home effectively. O'Keefe et al. (2016) identified that being married and having a car in the household is associated with a higher likelihood of telecommuting as well. These results were reaffirmed by studies conducted during the COVID-19 pandemic. Brough et al. (2020) found a lower propensity to work from home during the COVID-19 outbreak among lower-income groups and the less educated; Bick et al. (2020) concluded that switching to remote work was much more prevalent among highly educated, high-income and Caucasian workers. Beck and Hensher (2020) show that the option of working from home is more available to middle- and high-income groups and men. Nevertheless, Balbontin et al. (2022) showed that those on very high incomes are less positive about working from home. The authors argue that these individuals may be managers who are not as positive about managing people who are working from home. Equally, however, they may also have sufficient income to overcome household constraints more easily and are thus not as appreciative of greater work flexibility.[3] Using data from 27 countries, Aksoy et al. (2022) found that employer expectations differ from worker expectations regarding the amount of work from home after the pandemic, with employers planning an average of 0.7 work from home (hereinafter WFH) days per week, but workers wanting 1.7 days. However, as WFH productivity increases, employers' plans for WFH levels after the pandemic rise sharply. The authors therefore conclude that WFH levels will continue to increase after the pandemic.

Studies in transportation science find a robust association between working from home and commuting distance and time or public transport availability.[4] We do not deny the existence of

[3] Respondent satisfaction with working from home during the COVID-19 pandemic depends on various factors as well. As Hensher et al. (2022) indicated, working from home could lead to a greater sense of worth and thus have positive wellbeing outcomes. There were, however, specific situations connected with lockdowns which had a negative impact on satisfaction with telecommuting, such as the presence of children attending online school from home (Tahlyan et al., 2022).

[4] The relationship between commuting distance and working from home during the COVID-19 pandemic is summarized by Melo and de Abreu e Silva (2017) and Fatmi et al. (2022), and commute time by Nurul Habib et al. (2012), Aksoy et al. (2022), Brown and Tousey (2023) and Mokhtarian and Salomon (1997). Most studies indicate that workers who work from home have longer commutes on average (Peters et al., 2004; Turcotte, 2010). Some researchers also found an association between telecommuting and living in cities with poor transport conditions, including access to public transport – the availability of bus and rail stops near the place of residence (Caulfield, 2015; Lister and Harnish, 2011; O'Keefe et al., 2016). Less dense urban forms as a factor supporting telecommuting were identified by Shabanpour et al. (2018), O'Keefe et al. (2016) and Caulfield (2015), among others. Shabanpour et al. (2018) also showed a higher propensity to work from home in areas where the

this kind of statistical association. Nevertheless, it is important to stress that commuting time or distance, car ownership and the location of an individual's place of residence can hardly be considered determinants. People have at least some choices over the location of their workplace and/or place of residence, at least from a longer-term perspective. Thus, these characteristics should be regarded as co-determined with working from home rather than determining it.

People generally expected to work more from home after the pandemic than in pre-pandemic times. Using panel data from Israel and the Czech Republic, Kogus et al. (2022) showed that about 19% of respondents in both countries intend to reduce the number of days of work away from home, while 6% intend to increase them. Consequently, a reduction of 6.5% and 8.7% in the number of commuting trips is expected in Israel and the Czech Republic respectively in the post-pandemic era. A study from the USA (Barrero et al., 2021) indicates that 20 percent of full workdays will be supplied from home after the pandemic ends, compared with just 5 percent prior to the pandemic. Salon et al. (2021) found that 26% of workers expected to telework at least a few times a week after the pandemic, which is double the share of the same group before the pandemic. Furthermore, this increased number of teleworkers may decrease car commute kilometers by approximately 15% and public transport commute trips by 40%. A similar impact on transport is described by Javadinasr et al. (2022), who argue that nearly half of employees anticipate having the option of telecommuting, of whom 71% expect to work from home at least twice a week after the pandemic, which could lead to a decrease in car traffic of 9% and public transport use of 31%.

2.2 Online Shopping Potential

The volume and frequency of online shopping had already been growing prior to the COVID-19 pandemic, and online transactional activities increased further in response to the anti-pandemic measures and pandemic fear (Tran, 2021). The proportion of individuals aged 16–74 in the EU who ordered or bought goods or services on the internet for private use was 68% in 2022, up from 54% in 2017 (Eurostat, 2022b). Up to 2018, those aged 25–54 accounted for the highest share of online shoppers, second only to the youngest age group (16-24), which overtook the EU average level in 2019; this represents an increase of 29 percentage points in 2010–2020. In 2020, the same level of online shopping was recorded for the two age groups (Eurostat, 2022b).

E-commerce usage differs across types of goods. Shopping for groceries used to be the most frequent purpose of going on a shopping trip as it is best to inspect the physical attributes of groceries in person (Suel and Polak, 2017). However, there was a significant increase in online grocery purchases in the immediate aftermath of the COVID-19 outbreak. In contrast, equipment/devices/PC applications and books/DVD/software were already frequently purchased online before the outbreak and thus showed only a slight increase during the pandemic (Kawasaki et al., 2022; Meister et al., 2023). Online shopping has a substantial substitution effect (Meister et al., 2023; Suel and Polak, 2017). However, Drummond and Hasnine (2022) argue that an increase in online shopping does not necessarily lead directly to a decrease in offline shopping; in other words, online and in-store shopping are not as indirectly proportional as might be expected.

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employment density is high – this may mean that companies located in central business districts offer more opportunities for telecommuting to save space and reduce energy consumption.

Online shopping before and during the COVID-19 pandemic was influenced by a range of factors, the most predominant being access to electronic devices, delivery times (Strauss et al., 2021), and delivery costs (Schmid and Axhausen, 2019; Meister et al., 2023). The research further indicates that higher-income households benefit from online shopping more than lower-income households (Figliozzi and Unnikrishnan, 2021). There was also a substantial difference in the way in which online shopping was used by different groups of the population. Other socioeconomic factors influencing the intensity of online shopping included age, gender and marital status (Truong and Truong, 2022), as well as education and ethnicity (Figliozzi and Unnikrishnan, 2021). Older households were less likely to do their grocery shopping online (Beck and Hensher, 2020; Brůhová Foltýnová and Brůha, 2024). Unlike in the case of teleworking, place of residence is not a significant factor in e-commerce (Kawasaki et al., 2022)[5]. Women and girls, individuals with more than one available vehicle, higher income groups, those with health constraints or those worried about the virus showed a higher tendency to choose online shopping as their primary mode of shopping during COVID-19.

3. Data and Stylized Facts

3.1 Data

In our research, we use a unique survey focusing on the online and out-of-home activities of Czech citizens during and after the COVID-19 pandemic.[6] The data were collected in four waves among the adult urban population (18+) in the pandemic years of 2020 and 2021, and the last, fifth, survey wave was conducted after the pandemic in June 2022. To be precise, questionnaire distribution took place on June 5–15, 2020 (1st wave), November 5–18, 2020 (2nd wave), May 10–24, 2021 (3rd wave), September 23–October 18, 2021 (4th wave), and June 22–July 22, 2022 (5th wave). Data collection proceeded using an online questionnaire distributed to a panel of respondents by a professional agency. Our survey employed a quota sampling strategy to control for geographical distribution, gender, age and education to reach a representative sample of the Czech urban population as a whole. It targeted the economically active population (employees, the self-employed and students).

The questionnaire consisted of two main sections. In the first part, the respondents were asked about socio-economic and demographic characteristics, including work status, travel-related characteristics and attitude-related statements to identify latent variables/factors. This section also evaluated the number of days the respondents thought they could work from home without compromising their efficiency/productivity, regardless of the pandemic. The second part contained a diary/log in which respondents were asked about activities carried out from home and out-of-

[5] Kawasaki et al. (2022) used panel data on Japanese consumers to describe the development of shopping behaviour during three time periods for a panel survey in the spring and autumn of 2020. They found that immediately after the COVID-19 outbreak, the frequency of going out to shop decreased. The frequency of going out to shop then increased but did not reach the pre-pandemic level. The stay-at-home duration differed with city size; more populated areas had a longer stay-at-home period than less populated areas. Secondly, e-commerce usage differed across types of goods. Grocery goods experienced a significant increase compared to those before COVID-19. However, the total share of e-commerce usage for grocery goods was still smaller than that for other goods.

[6] Almost identical surveys were conducted in the Czech Republic and Israel. We refer the reader to Kogus et al. (2022), who provide more details on both surveys' designs. In this paper, we use the Czech data only. Kogus et al. (2022) discuss work from home during the pandemic in both countries, while Brůhová Foltýnová et al. (2023) compare online shopping in both countries during and after the pandemic.

home activities: in waves 1 to 4, they reported their behavior during the pandemic and their expectations of what they would do after the pandemic. In the first wave, respondents also reported their behavior before the pandemic, while in the final, fifth wave, they only reported their actual behavior. Shopping was divided into two categories of goods: necessities – i.e., food and pharmacy goods, and other items, i.e., other goods not considered to be necessities.

All the respondents participated in the first wave of the survey, but not all participated in the later waves. Table 1 displays the number of respondents in each wave, along with selected socio-demographic characteristics.[7] The econometric analysis in the subsequent parts of the paper is conducted using the sample from the fifth wave[8] (as all these respondents also participated in wave 1 and we thus have information on their behavior before and after the pandemic).[9]

Table 1: Descriptive Statistics of Selected Socio-Demographic Traits During the Survey Waves

	I.	II.	III.	IV.	V.	All waves
No. of respondents	1103	805	703	704	607	477
% of respondents participating in the first wave	*100%*	*73%*	*64%*	*64%*	*55%*	*43%*
Female	521	367	317	327	270	210
% participating in the wave	*47%*	*46%*	*45%*	*46%*	*44%*	*44%*
Aged under 30	246	136	105	101	82	61
% participating in the wave	*22%*	*17%*	*15%*	*14%*	*14%*	*13%*
Aged 30–50	583	439	383	384	327	253
% participating in the wave	*53%*	*55%*	*54%*	*55%*	*54%*	*53%*
Aged over 50	274	230	215	219	198	163
% participating in the wave	*25%*	*29%*	*31%*	*31%*	*33%*	*34%*
No high school diploma	335	208	171	172	148	112
% participating in the wave	*30%*	*26%*	*24%*	*24%*	*24%*	*23%*
High school diploma	448	346	310	301	260	204
% participating in the wave	*41%*	*43%*	*44%*	*43%*	*43%*	*43%*
University education	320	251	222	231	199	161
% participating in the wave	*29%*	*31%*	*32%*	*33%*	*33%*	*34%*

Source: Authors' calculations based on the survey data

3.2 COVID-19 Pandemic in the Czech Republic

COVID-19 hit the Czech population several times in 2020 and 2021 with different intensities. The first known cases of COVID-19 appeared in the Czech Republic in February 2020. The disease then hit the Czech population in 2020 and 2021 in several waves, which differed in the number of cases and deaths. Increases in the number of cases and deaths were recorded mostly in spring 2020 (relatively insignificant as measured by reported cases), autumn 2020, spring 2021 and autumn

[7] The table includes those socio-demographic variables that are important predictors of online activities as identified by econometric models in subsequent parts of this paper.

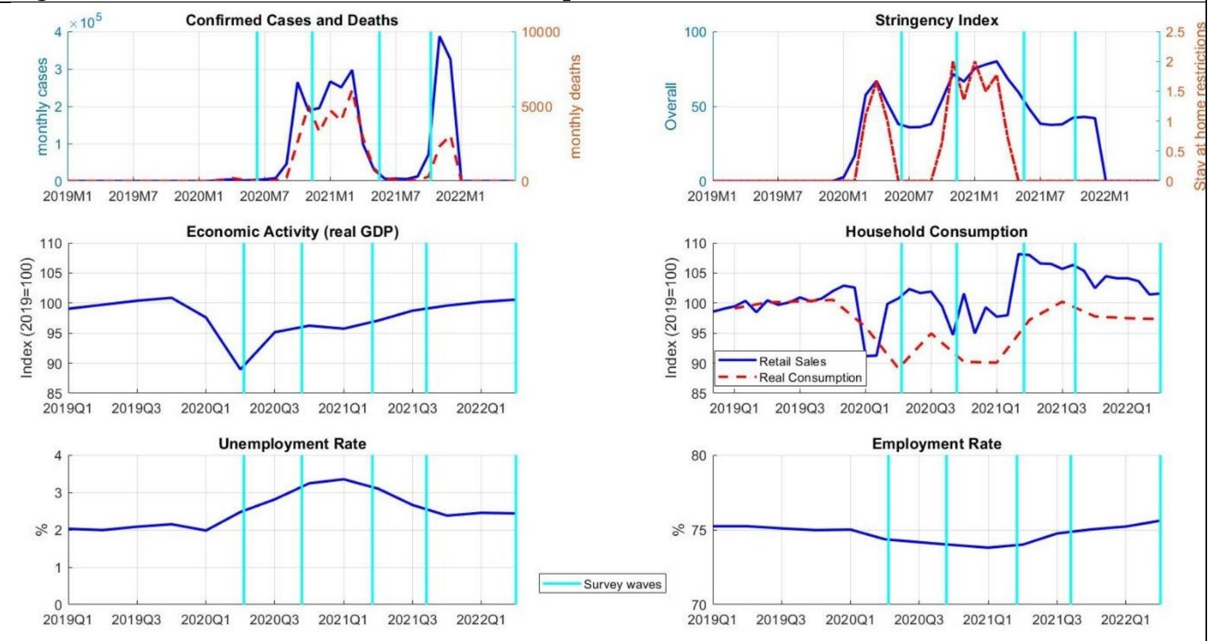
[8] We address a possible attrition bias in Appendix C.

[9] Descriptive charts in Appendix A that document the behavior during the pandemic use the sample of only those respondents who participated in all survey waves.

2021. The time series of the number of reported cases and deaths are displayed in the upper left-hand chart in Figure 1. In the chart, we also denote the dates of the five waves of our survey.

The stringency of government restrictions changed several times during the pandemic. On 12 March 2020, the government imposed a lockdown and people were urged to stay at home as much as possible. The main restrictions during the first peak period (mid-March to mid-April 2020) included social isolation and distancing, restriction of free movement, compulsory face masks and (social) regulation for businesses such as restaurants, accommodation services and retail services. The restrictions were moderated in May and further in June 2020. Various restrictions were reintroduced several times during 2020 and 2021 and then moderated again depending on disease dynamics. The upper right-hand chart in Figure 1 displays the overall stringency index (left-hand axis) and the stringency index related to stay-at-home restrictions (right-hand axis); see Hale et al. (2021) for the methodology behind these indices.

Figure 1: COVID-19 Pandemic in the Czech Republic



Source: Authors' calculations

Economic activity, consumer demand and the labor market were hit by the pandemic. Economic activity measured by real GDP fell dramatically in spring 2020 and then started slowly returning to its pre-pandemic level (see the lower left-hand chart in Figure 1). Initially, all sectors in the economy were similarly hit, but from autumn 2020, the most restrictions were imposed on services and retail: industry was, to a large degree, insulated from the restrictions. Consumer demand also fell initially, and its recovery was non-monotonous as can be seen from the middle right-hand chart. The non-monotonic dynamics of real household consumption and the retail sales index followed the dynamics of various government restrictions. Along with the fall in economic activity, the unemployment rate increased during the pandemic (see the lower right-hand chart in Figure 1); however, it remained well below 4% during the whole period, i.e., low by the standards of advanced countries. Similarly, the decrease in the employment rate was rather moderate.

3.3 Descriptive Statistics

The pandemic substantially influenced the way in which various activities were carried out. Working moved to the online environment for jobs which could be conducted from home. Table 2 reports the distribution of hours per week of WFH before and after the pandemic. Apparently, the number of respondents who reported zero WFH fell, as did the number of respondents who worked from home less than 10 hours per week. On the other hand, the number of respondents who worked from home 10 to 30 hours per week increased. The overall distribution shifted to more WFH; this shift can be summarized by the ordinal effect size,[10] which is significantly greater than 0.5.[11] Correspondingly, the distribution of out-of-home working shifted to lower numbers of hours per week as can be seen from Table 3 (the ordinal effect size is significantly lower than 0.5).

Table 2: Working from Home Before and After the Pandemic

Teleworking	Before	After
Never	59%	56%
Less than 10 hours a week	24%	22%
10 to 30 hours a week	8%	13%
More than 30 hours a week	8%	8%
Ordinal effect size		*0.55*

Table 3: Out-of-Home Working Before and After the Pandemic

Out-of-home working	Before	After
Never	4%	7%
Less than 10 hours a week	5%	7%
10 to 30 hours a week	10%	16%
More than 30 hours a week	70%	60%
Ordinal effect size		*0.42*

Source: Authors' calculations

A shift to full WFH is rare. In most cases, the respondents increased the number of hours they worked from home, retaining some out-of-home work. In fact, the share of respondents who reported zero out-of-home work increased only slightly (see the first row in Table 3) and the share of respondents working from home more than 30 hours per week was the same as before the pandemic.

[10] An ordinal measure of effect size is a simple and useful way to describe the difference between two ordered categorical distributions. This measure summarizes the probability that an outcome from one distribution Y_1 falls above an outcome from another distribution Y_2. It is defined as $Prob(Y_2>Y_1)+1/2Prob(Y_2=Y_1)$ and takes a value between 0 and 1. For two identical distributions and for distributions symmetrical around the common mean, it takes the value 0.5. If it is higher than 0.5, the distribution Y_2 dominates the distribution Y_1, and vice versa if it is below 0.5. See, e.g., Agresti (1981) for a more detailed discussion. Throughout the paper, the second distribution is the distribution of responses after the pandemic, while the first (benchmark) distribution is the distribution of responses before the pandemic.

[11] Throughout this paper, we use bootstrap to test whether the sample ordinal effect size is significantly different to 0.5. If not stated otherwise, the significance level for the ordinal effect size is 5%.

The frequency of online shopping increased after the pandemic. Table 4 displays the frequency of online shopping before and after the pandemic for two categories of goods. We see a huge fall in the number of respondents reporting that they never shop online, while the number of respondents who reported at least some online shopping increased for both categories analyzed in this paper. On the other hand, the number of respondents reporting frequent online shopping (at least 3 times a week) was almost the same. The ordinal effect size is significantly greater than 0.5 for both categories of goods.

Table 4: Online Shopping Before and After the Pandemic

Online shopping	Necessities		Other items	
	Before	After	Before	After
Never	53%	43%	23%	17%
Less than once a week	37%	42%	63%	70%
Once or twice a week	9%	13%	14%	12%
More than 3 times a week	1%	2%	1%	1%
Ordinal effect size		*0.56*		*0.52*

In-store shopping became less frequent after the pandemic, at least for necessities (see Table 5). The number of respondents shopping for necessities 3 times a week or more fell, and the ordinal effect size is significantly lower than 0.5.

Table 5: In-Store Shopping Before and After the Pandemic

Out-of-home shopping	Necessities		Other items	
	Before	After	Before	After
Never	0%	0%	9%	5%
Less than once a week	6%	8%	71%	79%
Once or twice a week	44%	55%	19%	15%
More than 3 times a week	50%	37%	2%	1%
Ordinal effect size		*0.39*		*0.50*

Source: Authors' calculations

The online activities considered here are correlated across respondents both before and after the pandemic. Figure 2 shows the distribution of frequency of online shopping depending on the WFH status. The bar charts are organized as follows. The first column shows the distribution of online shopping for all the respondents (it corresponds to Table 4), and the second column is the distribution of online shopping for respondents who did not report any hours of WFH. The third column shows this distribution for respondents who reported at least some WFH. Apparently, those who reported at least some WFH did more shopping online than those who did not work from home at all.[12] This holds for online shopping for necessities as well as for other items. In the subsequent section, we provide evidence that some socio-demographic characteristics (mainly age and education) are determinants of both working from home and shopping from home. In Section 5, we

[12] Interested readers may wonder whether the opposite holds too, i.e., whether those who work from home do less in-store shopping. It turns out that this is indeed true in the case of shopping for necessities. The situation for in-store shopping for other items is mixed.

show that the positive correlation between the two online activities remains even after adjusting for age and education.

Figure 2: Frequency of Online Shopping Conditional on Working from Home

Source: Authors' calculations

4. Identification of Socio-Demographic Characteristics Related to Online Activities

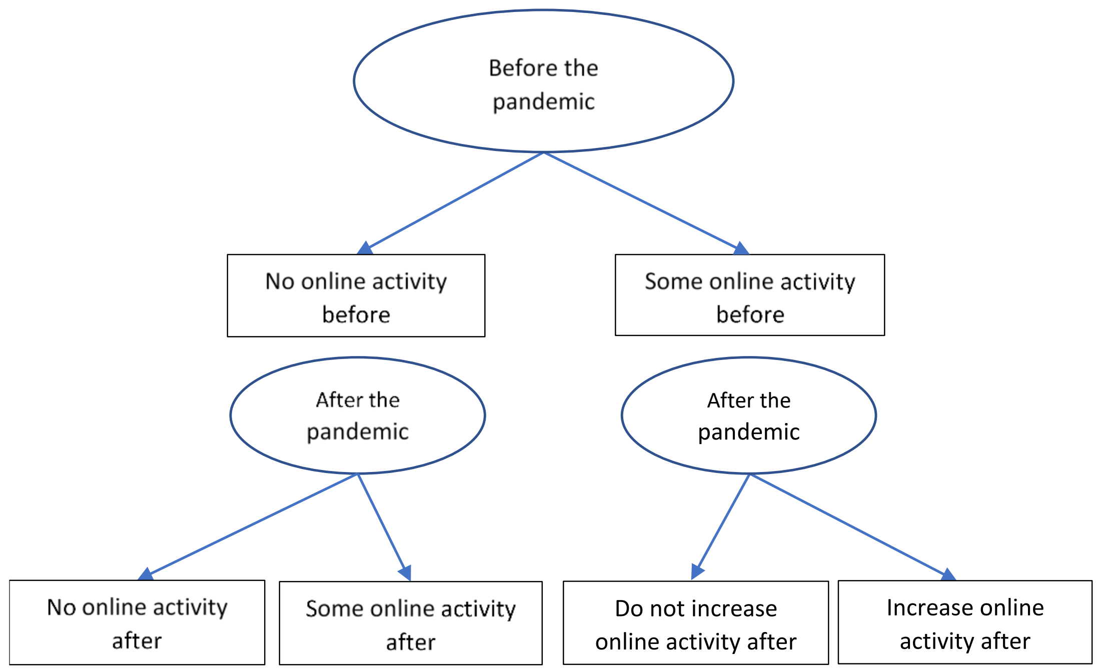
Who can be expected to engage more in online activity after the COVID-19 pandemic? The previous section documents an overall increase in online activity. In this part of the paper, we identify the socio-demographic characteristics of those who are likely to engage more in online activity.

To answer the question, we estimate a sequential logit model that identifies those who engaged in online activities before the pandemic, those who started to do so after the pandemic and those who increased their online activities. The structure of the sequential logit model[13] is displayed in Figure 4. In the upper level of the model, we identify those respondents who engaged in WFH or online shopping before the pandemic. In the first lower level, we identify those respondents who expected to engage in some online activity conditional on their non-usage before the pandemic. In the second lower level, we determine those respondents who expected to increase their level of online activity after the pandemic relative to their pre-pandemic level conditional on their usage before the pandemic. We use a forward-selection procedure to find the predictors to be included in the model. The set of variables that could enter the model was inspired by the literature

[13] See Amemiya, (1985), pp. 310–311, or Liao, (1994), pp. 25–37, for a general discussion on sequential logit models.

in Section 2 and includes gender, age, education, family status (married, single, number and age of children), location, car ownership, job type, industry and respondents' attitudes.[14]

Figure 3: Sequential Logit Model



Working from home before the pandemic was related mostly to education, job type and industry. The estimation of the model for WFH is provided in Table 6. Before the pandemic, the probability of at least some WFH was positively correlated with education (having a university degree increases the probability) and with having a high-mobility job, but negatively associated with having a job in a factory. The respondents that self-described as having a positive attitude to new technology also had a higher probability of WFH before the pandemic. Surprisingly, younger respondents under 30 had a lower probability, unless they had a high-mobility job.

The pandemic made WFH more attractive, especially for respondents with higher education. The probability of working at least some hours from home (conditional on not doing so before) is higher for respondents with a university degree, respondents working in the IT industry and respondents under 30. The right branch models the probability of working more from home conditional on doing so before the pandemic. This probability is higher for respondents with a higher level of education and those who live in families composed of one adult and at least one child under the age of 8, while respondents working in education do not see an increase in their WFH hours.

[14] The model is naturally estimated on the sample of respondents who participated in the first and last survey waves. The reader may wonder whether the estimation is biased due to attrition: respondents with certain characteristics may have a higher probability of not participating in the last wave. In Appendix C, we use the inverse probability weighting approach and re-estimate all models from this section. We conclude that our results are little affected by attrition.

Table 6: Sequential Logit Model for Working from Home

At least some work from home before the pandemic?	**Estimate**	SE	t stat	p value
(Intercept)	**0.20**	0.06	3.47	0.0
Age < 30	**-0.23**	0.07	-3.57	0.0
University degree	**0.25**	0.04	5.68	0.0
Job: High Mobility	**0.10**	0.07	1.47	0.1
Job: Factory	**-0.27**	0.07	-4.16	0.0
Positive attitudes towards new ideas	**0.27**	0.09	3.07	0.0
(Job: High Mobility)*(Age < 30)	**0.51**	0.25	2.07	0.0

At least some work from home after the pandemic? Conditional on not doing so before	**Estimate**	SE	t stat	p value
(Intercept)	**0.06**	0.04	1.33	0.1
Age < 30	**0.28**	0.07	4.15	0.0
High school diploma	**0.10**	0.05	1.79	0.0
University degree	**0.12**	0.06	1.78	0.0
Female living in a two-parent family	**0.20**	0.06	3.21	0.0
IT industry	**0.40**	0.11	3.77	0.0
Working in banking	**0.35**	0.13	2.71	0.0

More working from home after the pandemic? Conditional on doing so least sometimes before the pandemic	**Estimate**	SE	t stat	p value
(Intercept)	**0.15**	0.08	1.87	0.0
High school diploma	**0.16**	0.10	1.71	0.0
University degree	**0.24**	0.09	2.58	0.0
Family with one adult and a child/children under 8	**0.38**	0.23	1.66	0.1
Working in education	**-0.29**	0.10	-2.99	0.0

Source: Authors' calculations

Age and education are among the important determinants of online shopping for necessities. Younger respondents, respondents with a university degree and respondents with positive attitudes to new ideas had a significantly higher probability of reporting at least some online shopping for necessities before the pandemic (see the upper part of Table 7). This is similar to working from home. After the pandemic, the new users of online shopping are young men (the middle part of Table 7). Respondents who reported more online shopping for necessities after the pandemic are young, middle-aged (to a slightly lesser extent) and Prague residents (the lower panel of Table 7).

Age and education are also important determinants of online shopping for other items. While respondents with a university degree had a significantly higher probability of reporting at least some online shopping for necessities before the pandemic, the opposite is true for respondents over 50 (see the upper part of Table 8). After the pandemic, the new users of online shopping are respondents under 50. The probability of shopping for other items online is positively related to being under 30 and having at least a secondary education, and especially to having a university education (see the bottom part of Table 8).

Table 7: Sequential Logit Model for Shopping for Necessities

Shop for necessities from home before the pandemic?	**Estimate**	SE	t stat	p value
Intercept	**-0.80**	0.30	-2.65	0.0
Age > 50	**-0.40**	0.19	-2.14	0.0
University degree	**0.34**	0.18	1.87	0.0
Two-parent family with at least one child less than 8 years old	**0.87**	0.28	3.11	0.0
Positive attitudes towards new ideas	**0.86**	0.40	2.15	0.0
Shop for necessities from home after the pandemic? Conditional on not doing so before	**Estimate**	SE	t stat	p value
(Intercept)	**-0.31**	0.12	-2.58	0.0
Male * (Age < 30)	**0.71**	0.54	1.32	0.1
Shop for necessities more from home after the pandemic? Conditional on doing so at least sometimes before the pandemic	**Estimate**	SE	t stat	p value
(Intercept)	**-2.73**	0.45	-6.04	0.0
Age < 30	**1.01**	0.59	1.70	0.0
30 < Age < 50	**0.79**	0.46	1.72	0.0
Prague residents	**0.98**	0.35	2.81	0.0

Table 8: Sequential Logit Model for Shopping for Other Items

Shop for other items from home before the pandemic?	**Estimate**	SE	t stat	p value
Intercept	**1.02**	0.16	6.36	0.0
Age < 30	**0.95**	0.45	2.12	0.0
University degree	**1.09**	0.29	3.72	0.0
Two-parent family with at least one child less than 8 years old	**0.54**	0.26	2.10	0.0
Shop for other items from home after the pandemic? Conditional on not doing so before	**Estimate**	SE	t stat	p value
(Intercept)	**0.66**	0.29	2.29	0.0
Age > 50	**-0.28**	0.44	-0.64	0.5
Shop for other items more from home after the pandemic? Conditional on doing so at least sometimes before the pandemic	**Estimate**	SE	t stat	p value
(Intercept)	**-2.96**	0.49	-6.01	0.0
Age > 50	**-1.25**	0.61	-2.04	0.0
Positive attitudes towards new ideas	**1.38**	0.69	2.00	0.0

5. Multivariate Ordered Probit Model

Are the frequencies of the online activities analyzed in this paper mutually correlated even after controlling for socio-demographic characteristics? The model presented in the previous section has the advantage of having a straightforward interpretation of who used online activities before the pandemic (in terms of socio-demographic and economic characteristics) and who expected to use them after the pandemic. However, this is estimated separately for each activity and, therefore, cannot provide an answer to whether online activities are mutually correlated.

To answer this question, we employ a multivariate ordered probit model. It jointly models the reported behavior of working from home and online shopping before the pandemic as well as the behavior after the pandemic. The model is formulated as follows: The explained variables $y_{n,t}$ for a household *n* for an online activity *t* ($t \in$ {WFH before the pandemic, WFH after, online shopping for necessities before, online shopping for necessities after, online shopping for other items before, online shopping for other items after}) is determined as follows:

$$y_{n,t} = k \text{ if and only if } c_{k-1,t} < y^*_{n,t} \leq c_{k,t},$$

where $y^*_{n,t}$ is the unobserved latent continuous variable and $c_{k,t}$ are cut-offs that jointly determine the reported hours worked from home or the actual number of online shopping sessions (including the options "never" and "less than once a week").

As is usual, the model is cast in a linear latent variable framework. The latent variables $y^*_{n,t}$ follow a SUR (seemingly unrelated regression) model:

$$y^*_{n,t} = Z_n \beta_t + \xi_{n,t}$$

where Z_n is the vector of socio-demographic variables related to the respondent *n*, β_t are unknown coefficients and $\xi_{n,t}$ are unobserved random effects. We use four categories of observed variables for WFH and online shopping (the same as in Tables 2 and 4); hence, there are five cut-off values $c_{k,t}$. The cut-off values obey the natural ordering:

$$-\infty = c_{0,t} < c_{1,t} < c_{2,t} < c_{3,t} < c_{4,t} = \infty,$$

and as we include the intercept in the model, we use the usual identification constraints: $c_{1,t}=0$. Moreover, we impose equality of the cut-off values for each online activity before and after the pandemic[15]; the cut-off values may differ across online activities.

Random effects $\xi_{n,t}$ capture idiosyncratic variation in online activities across respondents, i.e., variation unexplained by the observed household characteristics Z_n. This random term is independent across respondents but correlated across activities. It is assumed that $\xi_{n,t}$ follows a normal distribution $N(0,\Xi)$, where the covariance matrix Ξ captures the correlation of online activities in time (before/after) as well as across activities.

The model is characterized by a set of parameters that have to be estimated. The goal of inference is to estimate the parameters β_t that determine how the observed household characteristics influence online activities, the covariance matrix Ξ of random effects $\xi_{n,t}$ that characterize idiosyncratic differences across respondents, and the cut-off values $c_{k,t}$. We use a set of age and education dummies (i.e., variables that pop up consistently in the nested logit model) as socio-demographic characteristics.

To estimate these parameters, we use a Bayesian MCMC algorithm. Thanks to the linear latent variable framework, the Gibbs algorithm can be derived as a straightforward extension of the Gibbs

[15] This means that the corresponding cut-off values for working from home before and after the pandemic equal each other, as do the corresponding cut-off values for online shopping for necessities and for other items. The reason for this constraint is that it would not otherwise be possible to compare in a straightforward manner the coefficients β_t for before and after the pandemic.

sampler for the multivariate probit model described, e.g., in Greenberg (2012). See Appendix B for more details, including the specification of the prior distributions.

Table 9: Multivariate Ordered Probit: Estimation of Coefficients β_t

	Teleworking				Shopping for necessities				Shopping for other items			
	Before		After		Before		After		Before		After	
	posterior mean	posterior s.e.	posterior mean	posterior s.e.	posterior mean	posterior s.e.	posterior mean	posterior s.e.	posterior mean	posterior s.e.	posterior mean	posterior s.e.
Intercept	-0.47	0.16	-0.63	0.17	-0.19	0.24	0.59	0.24	0.34	0.05	0.38	0.05
Age < 30	-0.53	0.20	0.08	0.18	-0.31	0.31	-0.19	0.30	0.04	0.07	0.05	0.07
Age > 50	-0.03	0.13	-0.14	0.13	-0.44	0.22	-0.38	0.21	-0.12	0.05	-0.12	0.05
High school diploma	0.22	0.16	0.48	0.17	0.25	0.26	-0.18	0.25	0.03	0.06	0.07	0.06
University degree	0.64	0.17	0.94	0.18	0.55	0.28	-0.09	0.25	0.14	0.06	0.11	0.06

Source: Authors' calculations

The estimation of the multivariate ordered probit model confirms that age and education are important determinants of online activities. This is apparent from Table 9, which summarizes the posterior means and posterior standard errors for coefficients β_t (we highlight in gray those coefficients whose posterior distribution has more than 95% mass above or below zero). Education was an important determinant of working from home before and after the COVID-19 pandemic, and the coefficients increased, i.e. the effect of education on WFH increased. Before the pandemic, young people WFH less frequently, which is no longer true after the pandemic. University education also increased the frequency of online shopping, especially before the pandemic. Being over 50 is a significant predictor of a low frequency of online shopping.

There is a clear positive correlation between the online activities. This can be seen in Table 10, which reports the posterior estimates for the matrix Ξ. The posterior means of the entries of the covariance matrix are displayed above and on the diagonal, and the posterior means of the corresponding correlation matrix are shown (in blue) below the diagonal. All the entries are positive and more than 98% of their posterior probability mass is located in the positive part of the real axis. Hence, we can conclude that online activities are positively correlated across respondents even after controlling for age and education.

Table 10: Posterior Estimation of Covariance Matrix Ξ for Random Terms

	Teleworking before	Teleworking after	Online shopping necessities before	Online shopping necessities after	Online shopping other before	Online shopping other after
Teleworking before	1.05	0.60	0.20	0.30	0.07	0.05
Teleworking after	0.57	1.05	0.30	0.37	0.07	0.07
Online shopping necessities before	0.12	0.18	2.84	1.26	0.41	0.22
Online shopping necessities after	0.17	0.21	0.44	2.93	0.24	0.29
Online shopping other before	0.18	0.17	0.62	0.36	0.16	0.08
Online shopping other after	0.15	0.20	0.36	0.48	0.53	0.13

Source: Authors' calculations

The ordered probit model is highly non-linear and the interpretation of the estimated coefficients is not straightforward. To alleviate this, we compute the effects of age and education on the distributions of working from home and online shopping. We conducted the following experiments. First, we asked how the distributions of online activities would change if all respondents with an elementary education obtained high school diplomas (everything else being equal). Second, we asked how the distributions would change if all respondents with high school diplomas had a university degree. Third, we asked how the distributions would change if all respondents in the sample below 30 were aged 30–50. Finally, we asked about the effects on the distributions if all respondents over 50 were aged 30–50. We caution the reader that the sole purpose of the experiments is to ascertain the strength of each variable in the model: these experiments should not be interpreted causally.

The education dummy related to high school diplomas has the greatest impact on the distribution of online activities. This can be seen in Tables 11–13 that display the results of the above-defined experiments and show the effect in percentage points of each of the distributions.

Table 11: The Effects of Model Variables on the Distributions of Working from Home

	Never	Less than 10 hours a week	10 to 30 hours a week	More than 30 hours a week
Effect of obtaining a high school diploma:				
Before the pandemic	-1.39	0.58	0.30	0.51
After the pandemic	-1.43	0.69	0.43	0.31
Effect of obtaining a university degree:				
Before the pandemic	-6.88	1.91	1.92	3.05
After the pandemic	-6.99	2.06	1.93	2.99
Effect of age < 30:				
Before the pandemic	-1.94	0.84	0.45	0.65
After the pandemic	-1.95	0.78	0.52	0.66
Effect of age > 50:				
Before the pandemic	-0.24	0.07	0.07	0.10
After the pandemic	-0.40	0.19	0.11	0.10

Table 12: The Effects of Model Variables on the Distributions of Online Shopping for Necessities

	Never	Less than once a week	Once or twice a week	More than 3 times a week
Effect of obtaining a high school diploma:				
Before the pandemic	-1.03	0.71	0.26	0.06
After the pandemic	-1.08	0.76	0.28	0.04
Effect of obtaining a university degree:				
Before the pandemic	-5.04	-16.20	1.21	20.03
After the pandemic	-4.88	-16.26	0.97	20.17
Effect of age < 30:				
Before the pandemic	-1.47	0.93	0.46	0.09
After the pandemic	-1.45	0.94	0.41	0.10
Effect of age > 50:				
Before the pandemic	-1.47	0.93	0.46	0.09
After the pandemic	-1.45	0.94	0.41	0.10

Table 13: The Effects of Model Variables on the Distributions of Online Shopping for Other Items

	Never	Less than once a week	Once or twice a week	More than 3 times a week
Effect of obtaining a high school diploma:				
Before the pandemic	-2.46	2.36	0.10	0.00
After the pandemic	-2.57	2.55	0.01	0.01
Effect of obtaining a university degree:				
Before the pandemic	-15.63	13.43	2.00	0.20
After the pandemic	-17.02	15.37	1.56	0.09
Effect of age < 30:				
Before the pandemic	-3.71	3.39	0.30	0.02
After the pandemic	-3.85	3.63	0.20	0.02
Effect of age > 50:				
Before the pandemic	-0.52	0.50	0.01	0.00
After the pandemic	-0.65	0.63	0.01	0.00

6. Conclusion

In this paper, we document that Czech households experienced an increase in working from home and online shopping after the pandemic relative to their pre-pandemic levels. This increase is more pronounced for online shopping, especially shopping for goods other than necessities. Age and education are significant predictors of these activities from home. In the case of WFH, job type is also an important factor. This is natural since some types of jobs cannot be carried out remotely.

Trends in online activities are important even for monetary policy. As argued in the Introduction, from a monetary policy perspective, an expansion of online activities may affect inflation dynamics, Phillips curve parameters, the business cycle properties of the labor market, the equilibrium interest rate and long-run productivity growth. It is therefore important to monitor and evaluate these trends.

We can expect to see a further increase in online activities in the future. WFH and online shopping can be regarded as a kind of new technology for households, a technology whose diffusion was fueled by the pandemic and related public-health measures. It is therefore not completely surprising that younger and more educated people are more likely to be the first to adopt these new behaviors.

We conclude by noting that there are studies related to this research that compare the potential of online activities after the pandemic in the Czech Republic and Israel using very similar data sets. For example, Brůhová Foltýnová et al. (2023) compare respondents' expectations about online shopping. The paper confirms our findings: in both countries, the main characteristics that increase the probability of online shopping are education, age and a positive attitude to new ideas or technologies. Kogus et al. (2022) find an expected increase in WFH of 10%–14% among those who work more than 20 hours a week (in both countries). This means that the WFH experience due to the COVID-19 pandemic has enabled some people to view working from home as viable.

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Appendix A: Behavior During the Pandemic

In this appendix, we provide a summary of the respondents' actual and expected online activities during each survey wave. During survey waves 1 to 4, respondents were asked about their actual online activities as well as their expectations after the pandemic.

Figure A1: Working From Home During the Survey Waves

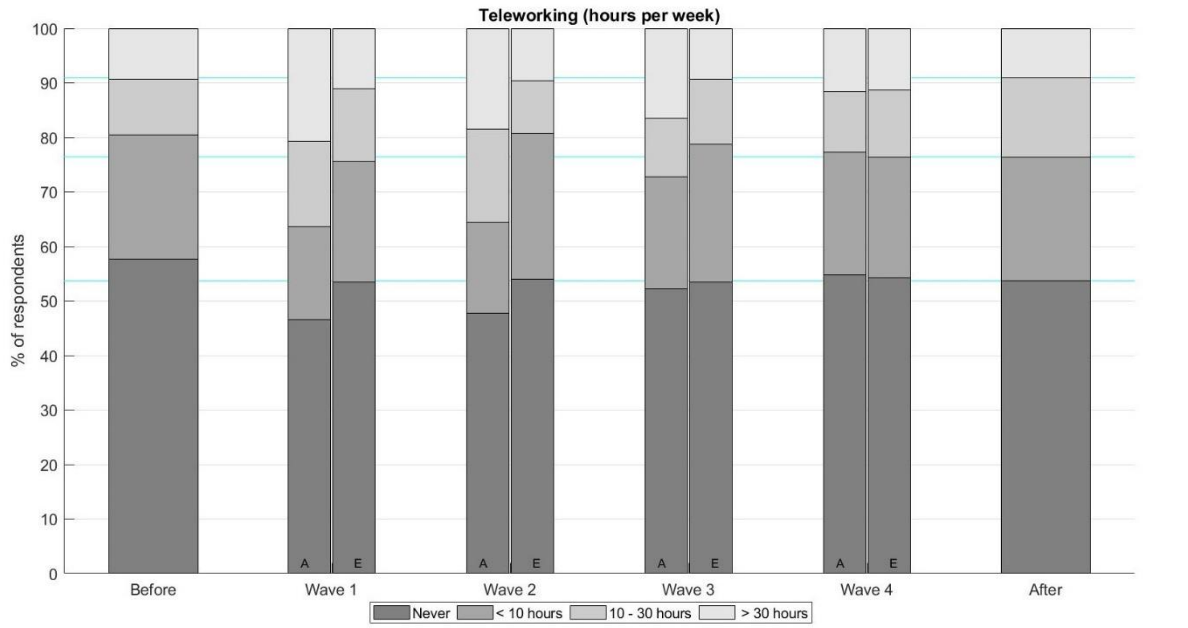

Figure A1 summarizes the survey results on WFH. The first column ("Before") summarizes the answers about the actual number of WFH hours before the pandemic, while the last column ("After") summarizes the results from the last survey wave. Each column corresponding to waves 1 to 4 has two sub-columns. The first one (with "A" at the bottom) gives the results for the actual number of hours spent working from home. The second one (with "E" at the bottom) gives the respondents' expectations about their number of hours of WFH after the pandemic.

Apparently, the first two waves witnessed more WFH hours than the later waves. This increase in WFH was partly reversed during later survey waves. The same is true for respondents' expectations. During survey waves 1 and 2, respondents expected to do more WFH than what they reported during the last wave as actual behavior. On the other hand, their expectations from the two later waves (3 and 4) match the actual behavior from the last survey wave surprisingly well.

A very similar pattern holds for online shopping. This can be seen in Figure A2, which is organized analogically to Figure A1. During the first two waves, we see an increase in the frequency of online shopping for both categories of goods. This increase is partly reversed during the two later waves. Again, the respondents' expectations about online shopping after the pandemic are very much in line with the actual frequencies collected during the last wave.

For policy purposes, it is also vital to know how and whether the pandemic changed the dominant mode of transport for those trips still taken. The information about dominant modes of transport (both actual and expected) is summarized in Figure A3. Apparently, the pandemic caused a shift from public transport to other modes of transport, especially to cars. This shift to cars was largely temporary: indeed, during the last survey wave, the share of respondents who reported the car as the dominant mode of transport for both commuting and in-store shopping was almost the same as before the pandemic. However, the share of respondents using public transport did not return to its former level, while active transport (walking and cycling) and car sharing/pooling regained their shares.[16]

Figure A2: Online Shopping During the Survey Waves

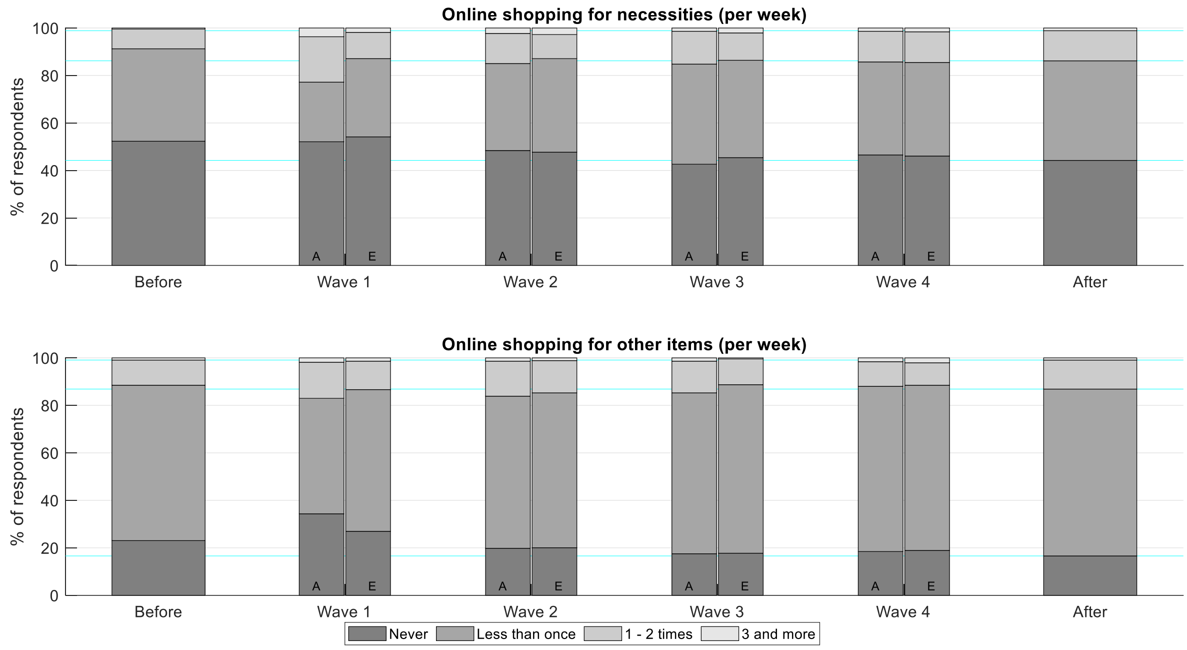

Figure A3: Dominant Mode of Transport for Commuting and In-store Shopping

[16] We also asked whether the dominant mode of transport for in-store shopping was influenced by WFH. Alipour et al. (2022) find a local spending effect in German data, i.e., those who work from home shop locally. Given this finding, we would expect our data to reveal that that working from home is associated with a higher probability of active travel. Our data, however, do not provide any such evidence. In the post-pandemic wave, the shares of dominant modes of transport used for in-store shopping for those who work at least a few hours a week from home are statistically indistinguishable from the shares for those who work fully out of home.

Appendix B: MCMC Sampler for an Ordered Multivariate Probit Model

In this appendix, we provide details about the estimation of the multivariate ordered probit model introduced in Section 5. We use an MCMC algorithm with 50,000 iterations, where the first 10,000 iterations are discarded.

The priors are non-dogmatic. We use the normal prior for coefficients $\beta_t \sim N(\beta_{0t}, \Omega_{0t})$, and we set a non-informative prior for all activities: $\beta_{0t} = \mathbf{0}$ and $\Omega_{0t}^{-1} = \mathbf{0}$. The prior for the covariance matrix of random terms is the inverse Wishart distribution, $\Xi \sim IW(R_0^{-1}, \nu_0)$ and we also set a non-informative prior: $R_0^{-1} = \mathbf{0}$ and $\nu_0 = 0$. As for the cut-off values, we need to specify only $c_{2,t}$ and $c_{3,t}$ (other cut-off values are imposed for model identification). We assume a joint prior with two marginal uniform priors subject to the constraint: $c_{2,t} < c_{3,t}$. The marginal priors are uniform $c_{2,t} \sim U(\chi_2^L, \chi_2^U)$ and $c_{3,t} \sim U(\chi_3^L, \chi_3^U)$. In our estimation, we set the following hyperparameters for cut-off values for all online activities: $\chi_2^L = 0.2$, $\chi_2^U = 2.5$, $\chi_3^L = 1.2$, $\chi_3^U = 4.5$.

The sampler switches between sampling the model parameters and the latent variables. The MCMC iterations are denoted by the superscript *(m)*. Before deriving the MCMC sampler, we use the following notation: β_0 is the vector created from stacked individual vectors β_{0t}, and $\Omega_0$is the blocked diagonal matrix composed of Ω_{0t} (and similarly for β). The vector y_n^* is a column vector with entries $y_{n,t}^*$, i.e., observed online activities for the respondent n.

Given the latent-variable structure of the model and the prior specification, it is a straightforward exercise to derive a Gibbs sampler. The Gibbs sampler iterates between the following steps:

- Given the latent variables $y_n^{*(m-1)}$ and other parameters of the model, sample the regression coefficients from the normal distribution $\beta^{(m)} \sim N(\beta_1, \Omega_1)$, with

  $$\Omega_1^{-1} = \left(\Xi^{(m-1)}\right)^{-1} \otimes \textstyle\sum_n Z_n^T Z_n \text{ and } \beta_1 = \Omega_1^{-1}\left(\Omega_0^{-1}\beta_0 + \sum_n \left(\Xi^{(m-1)}\right)^{-1} \otimes Z_n^T y_n^*\right).$$

- Given the parameters of the model and data, sample the latent variables from the multivariate truncated normal distributions with the covariance matrix equal to $\Xi^{(m)}$, the mean vector having the components $Z_n\beta_t$ and the truncation respecting data and the current iteration cut-off values. This is the step of the algorithm that is difficult and time consuming.
- Given the rest of the parameters and the latent variables, sample the covariance matrix $\Xi^{(m)} \sim IW(R_1^{-1}, \nu_1)$ with $\nu_1 = \nu_0 + N$ and
  $R_1^{-1} = \sum_n \left(y_n^{*(m)} - (\boldsymbol{I} \otimes Z_n)\beta^{(m)}\right)\left(y_n^{*(m)} - (\boldsymbol{I} \otimes Z_n)\beta^{(m)}\right)^T.$
- Given the rest of the parameters and the data, draw the cut-off values from the uniform distribution $c_{2,t}^{(m)} \sim U(\chi_{2,t}^L, \chi_{2,t}^U)$, $c_{3,t}^{(m)} \sim U(\chi_{3,t}^L, \chi_{3,t}^U)$ using the following parameters:

$$\chi_{2,t}^L = \max\left(\chi_2^L, \max_{\tau: y_{n,\tau=1}}\left(y_{n,\tau}^{*(m)}\right)\right),$$

$$\chi_{2,t}^U = \min\left(\chi_2^U, \min_{\tau: y_{n,\tau=2}}\left(y_{n,\tau}^{*(m)}\right)\right),$$

$$\chi_{3,t}^L = \max\left(\chi_3^L, \max_{\tau: y_{n,\tau=2}}\left(y_{n,\tau}^{*(m)}\right)\right),$$

$$\chi^U_{3,t} = \min\left(\chi^L_3, \min_{\tau: y_{n,\tau=3}}\left(y^{*(m)}_{n,\tau}\right)\right).$$

Appendix C: Inverse Probability Weighting Estimator

In this part of the paper, we address the question of whether there is attrition bias for the sequential logit models from Section 4. Attrition bias may arise as the models are obviously estimated on the sample of respondents who participated in both the first and last survey waves. One cannot estimate the model for those who chose not to participate in the last wave. If this choice is related to respondents' characteristics, the results may be biased.

We use the inverse probability weighting estimator to address this issue. First, we estimate the logit model to see which socio-demographic characteristics are systematically related to staying in the survey in the fifth wave.[17] Based on the fitted logit model, we compute the probability of staying in the fifth wave and re-estimate the sequential logit models from Section 4, when observations have weights that are the inverse of this probability. This means that respondents, who (according to their observed characteristics) have a low probability of staying in the fifth wave, receive higher weights.

First, we estimate a logit model to see which characteristics are associated with staying in the fifth wave of the survey. We look at the same set of respondents' characteristics and run the automatic stepwise procedure to select the appropriate regressors. The results are given in Table C1 below.

Table C1: Logit Model of the Probability of Staying in the Fifth Wave

	Estimate	SE	t stat	p value
Intercept	**0.92**	0.20	4.66	0.00
Age > 30	**-1.00**	0.16	-6.05	0.00
Age < 50	**0.78**	0.17	4.72	0.00
Elementary education	**-0.79**	0.14	-5.61	0.00
Female living in a two-parent family	**-0.35**	0.16	-2.15	0.03
Positive attitudes towards new ideas	**-0.62**	0.28	-2.21	0.03

We then use the inverse of the fitted probabilities in replicating the sequential logit model from Section 4. The results are displayed in Tables C2 to C4. When compared to Tables 6 to 8, the changes in estimated coefficients and their significance are minor and our interpretation need not be changed.

[17] See Fitzmaurice (2015) for a discussion of inverse probability weighting.

Table C2: Sequential Logit Model for Working from Home – Inverse Probability Weighting

At least some work from home before the pandemic?	**Estimate**	SE	t stat	p value
(Intercept)	**0.21**	0.06	3.58	0.0
Age < 30	**-0.23**	0.05	-4.14	0.0
University degree	**0.25**	0.04	5.71	0.0
Job: High mobility	**0.12**	0.07	1.62	0.1
Job: Factory	**-0.26**	0.06	-4.03	0.0
Positive attitudes towards new ideas	**0.24**	0.09	2.72	0.0
(Job: High mobility)*(Age < 30)	**0.39**	0.19	2.09	0.0

At least some work from home after the pandemic? Conditional on not doing so before	**Estimate**	SE	t stat	p value
(Intercept)	**0.05**	0.04	1.27	0.2
Age < 30	**0.25**	0.06	4.29	0.0
High school diploma	**0.11**	0.05	1.98	0.0
University degree	**0.15**	0.06	2.30	0.0
Female living in the two-parent family	**0.18**	0.06	2.94	0.0
IT industry	**0.41**	0.11	3.68	0.0
Working in banking	**0.36**	0.14	2.61	0.0

More working from home after the pandemic? Conditional on doing so at least sometimes before the pandemic	**Estimate**	SE	t stat	p value
(Intercept)	**0.18**	0.07	2.42	0.0
High school diploma	**0.14**	0.09	1.55	0.1
University degree	**0.22**	0.09	2.53	0.0
Family with one adult and a child/children under 8	**0.39**	0.21	1.84	0.0
Working in education	**-0.30**	0.09	-3.19	0.0

Table C3: Sequential Logit Model for Shopping for Necessities – Inverse Probability Weighting

Shop for necessities from home before the pandemic?	**Estimate**	SE	t stat	p value
Intercept	**-0.68**	0.23	-3.00	0.0
Age > 50	**-0.32**	0.15	-2.13	0.0
University degree	**0.43**	0.14	3.13	0.0
Family with with at least one child less than 8 years old	**0.87**	0.21	4.26	0.0
Positive attitudes towards new ideas	**0.57**	0.29	1.95	0.0

Shop for necessities from home after the pandemic? Conditional on not doing so before	**Estimate**	SE	t stat	p value
(Intercept)	**-0.34**	0.09	-3.71	0.0
Male * (Age < 30)	**0.83**	0.32	2.62	0.0

Shop for necessities more from home after the pandemic? Conditional on doing so at least sometimes before the pandemic	**Estimate**	SE	t stat	p value
(Intercept)	**-2.76**	0.37	-7.50	0.0
Age < 30	**1.07**	0.42	2.53	0.0
30 < Age < 50	**0.78**	0.37	2.08	0.0
Prague residents	**1.10**	0.25	4.33	0.0

Table C4: Sequential Logit Model for Shopping for Other Items – Inverse Probability Weighting

Shop for other items from home before the pandemic?	**Estimate**	SE	t stat	p value
Intercept	**1.00**	0.13	7.88	0.0
Age < 30	**0.89**	0.27	3.31	0.0
University degree	**1.12**	0.23	4.85	0.0
Two-parent family with at least one child less than 8 years old	**0.62**	0.20	3.15	0.0
Shop for other items from home after the pandemic? Conditional on not doing so before	**Estimate**	SE	t stat	p value
(Intercept)	**0.64**	0.21	3.07	0.0
Age > 50	**-0.26**	0.35	-0.74	0.4
Shop for other items more from home after the pandemic? Conditional on doing so at least sometimes before the pandemic	**Estimate**	SE	t stat	p value
(Intercept)	**-2.67**	0.36	-7.49	0.0
Age > 50	**-1.49**	0.44	-3.37	0.0
Positive attitudes towards new ideas	**1.06**	0.50	2.13	0.0

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