Pandemic Consumption*

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Abstract

This paper examines how households adjusted their consumption behavior in response to the COVID-19 infection risk during the early phase of the pandemic and without consumption lockdowns. We use a monthly consumption survey specifically designed by the German Statistical Office, covering the second wave of COVID-19 infections from September to November 2020. Households reduced their consumption expenditures on durable goods and social activities by 24 percent and 36 percent, respectively, in response to one hundred additional infections per one hundred thousand inhabitants per week. The effect was concentrated among the elderly, whose mortality risk from COVID-19 infection was arguably the highest.

Key words: consumption, health risk, pandemic, COVID-19, survey data
JEL-Codes: D12, E21, E32, I12

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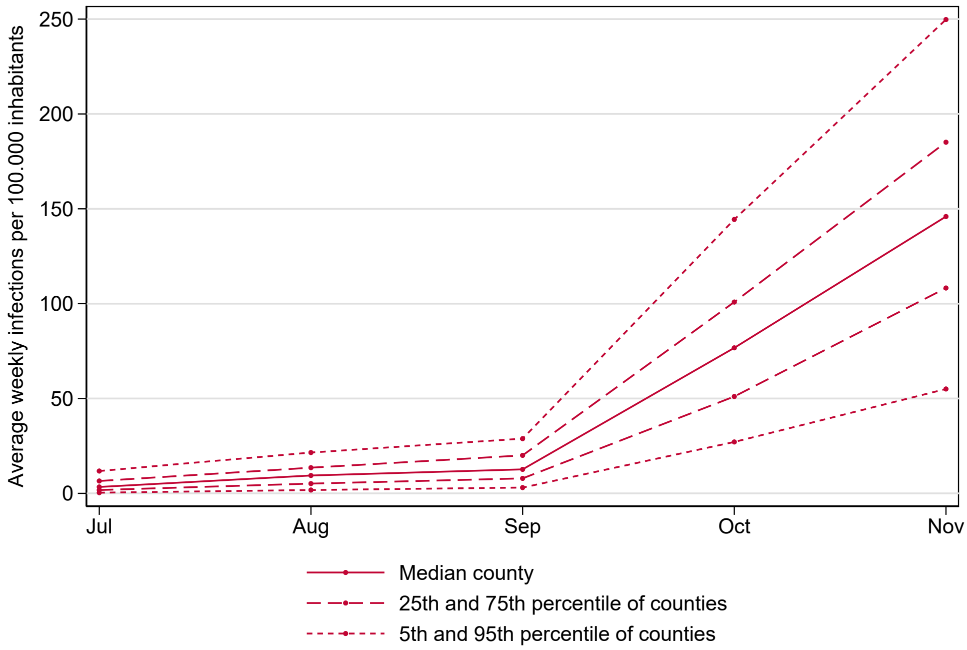
1 Introduction

In the year 2020, the COVID-19 pandemic had spread throughout the world with catastrophic economic consequences. To protect public health, many governments decided to restrict not only production, but also sales and consumption. These measures were controversial, as governments faced a trade-off between the level of economic activity and the health consequences of COVID-19 infections. A central question in the debate was how and which households would respond to the risk of infection in the absence of government intervention. Would all households voluntarily curb their consumption to protect themselves and others, or would only the most vulnerable households reduce their consumption? Those who opposed non-pharmaceutical public health measures argued that people would protect themselves optimally against a COVID-19 infection. Therefore, government intervention would lead to an excess loss of economic activity. Those in favor of public health measures emphasized the following consumption-infection externality: consumption that involves human interaction leads to more infections, which further increases the risk of infection for everyone and thus leads to higher mortality among vulnerable strata of the population. In this case, a lack of government interventions could lead to an excess loss of economic activity: In the laissez-faire equilibrium, the number of infections would rise rapidly, leading to an even greater reluctance to consume, at least among the most vulnerable. Economists have informed this debate on the basis of structural models that link consumption behavior and infection risk in both directions in the various strata of the population (e.g., Kaplan, Moll, and Violante, 2020, discuss in detail the pandemic possibility frontier that results). What was missing then, and is still missing, are reliable estimates of the laissez-faire consumption response of households to COVID-19 infection risk, i.e., their response in the absence of direct government restrictions.

In this paper, we use high-quality, high-frequency, and granular German household consumption data to shed light on this issue. We find that households significantly reduce their spending on social consumption (recreational activities outside the home, sports, tickets, restaurants, etc.) and on consumer durables when local infection risks are higher. An increase in the weekly infection risk by one hundred additional weekly infections per one hundred thousand inhabitants in the fall of 2020 reduced social consumption by 36 percent and durable consumption spending by 24 percent. The effect on total consumption is smaller and statistically insignificant, suggesting some substitution to other categories. We also show that this response in consumption is driven by the response of the elderly. In addition, we find that the consumption response is stronger in places with higher social capital. We interpret the former as evidence of a self-interested behavioral response and the latter as an indication of pro-social motives. We find no evidence that the expected local economic fallout of the pandemic drives the consumption restraint. For durable consumption, we document that the overall decline is driven by a decrease in the likelihood of making large purchases (relative to income), which, presumably, require a personal inspection of the good or advise by a sales professional.

After Germany experienced the first wave of the COVID-19 pandemic in spring 2020, infection rates began to rise again in October 2020, after a relatively calm summer. This resurgence occurred nationwide, but spatially asynchronous, see Figure 1. This second wave of the COVID-19 pandemic prompted the German government to impose a second lockdown on November 2, 2020, including the closure of

Figure 1: Infection rates across time and counties (Kreise)



Notes: Sample statistics of the cross-sectional distribution of infections relative to population across counties by month. Source: *Robert-Koch-Institut*.

restaurants, bars, clubs, and other recreational venues.[1]

We exploit this spatially asynchronous unfolding of the second wave of COVID-19 between September and October 2020 to identify the effect of local infection risk on consumer behavior. We focus on October because there was a combination of both elevated and spatially heterogeneous infection risk, but without significant non-pharmaceutical interventions by the government. In contrast, consumption in November was influenced by such government restrictions. However, our estimates allow us to model a counterfactual scenario and gauge how large the voluntary decline in social consumption would have been in November without the lockdown. Given the higher number of infections, averaging 150 per hundred thousand inhabitants per week, the predicted decline in social consumption (relative to no infections) for November would have been about 50 percent. This compares well with the actual decline between September and November, meaning that the lockdown had little or no additional impact on social consumption. For consumer durables, we show that actual consumption development was better than the predicted counterfactual. Taken together, these two results are compatible with the view that the lockdown did not lead to sizable excess economic losses.

Our empirical strategy requires consumption data that are both comprehensive and, due to the fast-paced dynamics of pandemics, of relatively high frequency. In particular, survey (as opposed to scanner and credit card) data are uniquely suited to capture social and durable goods expenditures in combination with numerous sociodemographic and socioeconomic data.[2] We therefore build on the *Sonderbe-*

[1] Throughout this paper, we use the term "lockdown" somewhat loosely to mean any non-market-based government restriction on social consumption activities, not necessarily a ban on free movement.

[2] In many countries, for sure in the German context, cash payments for social consumption have been the norm, for

fragung zum Konsum privater Haushalte 2020, hereafter referred to as the Consumption Survey or, simply, survey. This ad hoc survey was developed by the German Federal Statistical Office (FSO) on behalf of the German Federal Ministry of Finance and with our conceptual input. From August to December 2020, the FSO conducted a monthly survey on the consumption behavior of German households. In addition to sociodemographic and socioeconomic data, the survey collected aggregate and disaggregated household consumption data retrospectively for the preceding month. Combining these data with the official disaggregated infection counts and spatial controls, we estimate a consumption equation with the coefficient on the number of local COVID-19 infections as our object of interest. The reference date for infections recorded by the German Center for Disease Control (*Robert-Koch-Institut*) is typically the date of a positive test.

The literature on the economic effects of the pandemic and the pandemic policy measures is large (see, for example, Atkeson, Droste, Mina, and Stock, 2020; Coibion, Gorodnichenko, and Weber, 2020; Cutler and Summers, 2020; Glover, Heathcote, Krueger, and Ríos-Rull, 2020; Bodenstein, Corsetti, and Guerrieri, 2022; Krueger, Uhlig, and Xie, 2022; Fuchs-Schündeln, Krueger, Ludwig, and Popova, 2022; Eichenbaum, de Matos, Lima, Rebelo, and Trabandt, 2023; Fuchs-Schündeln, Krueger, Kurmann, Lale, Ludwig, and Popova, 2023), but precise empirical estimates of behavioral responses to the risk of infection are still rare.[3] Yet this response is key to understanding the macroeconomic consequences. One of the first macroeconomic papers on the COVID-19 pandemics is Eichenbaum, Rebelo, and Trabandt (2021). They calibrate their model so that households reduce aggregate consumption by less than 14 percent at the model's predicted pandemic peak of about 5,000 infections per week per hundred thousand inhabitants (their Figures 1 and 2). Eichenbaum, Rebelo, and Trabandt (2022a,b) use consumption-infection elasticities similar to those in their earlier paper. Our point estimate for total consumption, while insignificant, is much higher: 5 percent per 100 weekly infections per hundred thousand inhabitants. Kaplan et al. (2020) emphasize that the response of consumption expenditures is expected to be

some, in particular older, strata of the population prior to the pandemic.

[3]The paper closest to ours is Horvath, Kay, and Wix (2023), which uses U.S. credit card data to estimate the year-over-year change in credit card spending due to county-level COVID-19 infection risk. Because here the effects on consumption spending are concentrated in the first few months of the pandemic, assumptions are needed to disentangle the effect of COVID-19 infection risk from the effect of non-pharmaceutical interventions. Consistent with our results, Horvath et al. (2023) finds that the effect of COVID-19 infection risk is the larger one, a finding that is also supported by Goolsbee and Syverson (2021) which uses cell phone data to track consumer traffic, though not actual spending data. By contrast, our paper uses survey data, which allows for a broader notion of consumption spending and allows us to study more dimensions of consumer (age and wealth) and consumer good heterogeneity, and to address potential threats to identification head-on. What is more, our survey is representative by design and thus avoids potential biases towards strata of the population that are more inclined to use credit card payments over cash. Baker, Farrokhnia, Meyer, Pagel, and Yannelis (2020), Andersen, Hansen, Johannesen, and Sheridan (2022), Eichenbaum et al. (2023), Emiliozzi, Rondinelli, and Villa (2023), using U.S., Danish, Portuguese, and Italian transaction-level spending data, respectively, all find substantial negative consumption responses after the onset of the pandemic, but the focus here is not on the causal identification of the effect of COVID-19 infection risk, but rather a time-series interest on the overall causal effects of the pandemic (including those of the pandemic policy measures) with, depending on the study, numerous results on consumer and consumer good heterogeneity. Having said this, Andersen et al. (2022) also document that health risk is the strongest factor in driving the differential response across households during this first wave of the pandemic. Finally, von Gaudecker, Holler, Janys, Siflinger, and Zimpelmann (2021) estimates, again using mostly time series variation, the labor supply response to the pandemic in the Netherlands.

larger for those activities that expose a household more to infection, such as social consumption. Their macro-epidemiological model shows a slower evolution of the epidemic than Eichenbaum et al. (2021), implying that, under laissez-faire, infections peak at about 1,500 infections per week per hundred thousand inhabitants. At this peak, they find a 40 percent drop in social consumption, see their Figures 4(b) and (e). In between these estimates is the model of Krueger et al. (2022) calibrated to Swedish data. They estimate a 70 percent reduction in consumption sectors with higher contagion risk (e.g., social consumption) at the peak, i.e., weekly infection rates of 6,000 per hundred thousand inhabitants.

Our estimated consumption response is stronger, predicting that durable and social consumption would decline by more than 95 percent at infection rates as high as in Kaplan et al. (2020). In other words, our estimated consumption responses imply much less of a difference in consumption between a consumption lockdown and the voluntarily chosen consumption decline in a laissez-faire regime.

The remainder of the paper is organized as follows: Section 2 describes the data we use. Section 3 presents the results of our analysis. Section 4 concludes. Various appendices follow.

2 Data description

The consumption survey was conducted online from August to December 2020 in five waves (without a panel structure) at one-month intervals. The FSO outsourced this task to the *Gesellschaft für Konsumforschung* (GfK), an independent institute specializing in such consumption surveys.[4]

At the heart of the survey are detailed questions on the household's actual consumption in the previous month. These questions are supplemented by detailed socioeconomic and sociodemographic information on the household (head).

Survey participants were drawn by GfK from an *Online Access Panel*, a continuously updated database of sociodemographic profiles of identity-checked individuals who are potentially willing to provide information. It has approximately 40,000 active entries. From this, a stratified sample was drawn based on age, gender, household size, and Nielsen areas.[5] Participation in the survey was voluntary (see Bachmann, Bayer, and Kornejew, 2021, for a detailed data description and discussion of data quality). Sampling probabilities were determined from the distributions of the *2019 Mikrozensus*, excluding individuals younger than 18 or older than 74. Individuals interviewed once were excluded from the sample of subsequent waves. The raw data were first adjusted by GfK using standard procedures[6] and made available to the FSO for the construction of other variables. In addition, the sample weights of the consumption survey were adjusted to match the population of the *2019 Mikrozensus* with respect to the multivariate distribution of household size, household type,[7] nominal net household income (categorical) and number of children under 18 living in the household. The residence of the household is recorded as its three-digit postal code. We focus on the survey months of October and November,

[4]The GfK provides the German input to the EU-harmonized consumer sentiment survey.

[5]Nielsen areas are spatial subdivisions of federal states based primarily on statistical considerations.

[6]For example, duplicates were filtered statistically and by IP address matching to ensure that no two individuals were from the same household.

[7]Household types are: singles, couples without children, couples with children, and single parents.

which record expenditures in September and October, respectively, in order to avoid direct lockdown effects (on expenditures in November) and holiday effects in the summer months. This leaves us with about 7,000 observations after some data cleaning. Tables A.1 and A.2 in Appendix I provide the sample sizes and an overview of our sample selection procedure. Appendix II provides summary statistics of our data. Appendix IV shows the survey questions we use in an English translation.

To validate the quality of the consumption survey, Bachmann et al. (2021) and Bachmann et al. (2022) compare the consumption survey against the 2018 *Einkommens- und Verbrauchsstichprobe* (EVS, sample survey of income and consumption expenditures, broadly like the CEX in the US). Due to its methodological depth and large sample, the EVS provides the most reliable and at the same time detailed picture of the consumption behavior of German households. Since the EVS is only conducted every five years, most recently in 2018, it, however, cannot itself be used to evaluate the consumption effects of the pandemic.

For the data on local COVID-19 infections, we rely on the official records provided by the *Robert-Koch-Institut* (the German analog of the Center for Disease Control). We aggregate the daily infection data at the *Kreis/kreisfreie Stadt* (county) level to the monthly level and match them to the three-digit postal code level of the respondent.[8] Lastly, we add county-level information on population density and information on the number of hotel beds, a measure of tourism intensity.

3 Results

3.1 Empirical patterns at the aggregate level

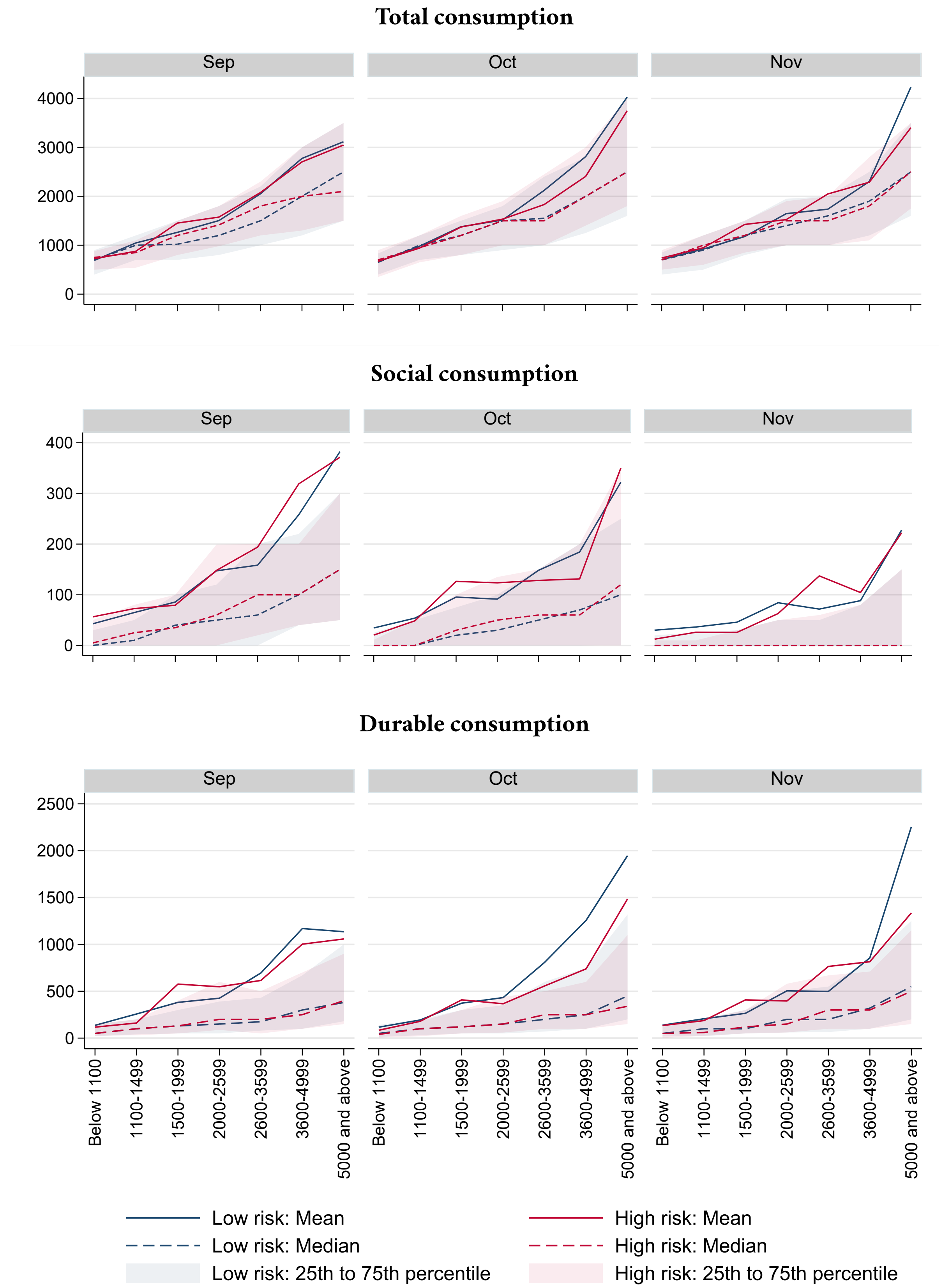
We start with a visual inspection of the changes in the Engel curves over the months September to November 2020, see Figure 2. The figure displays the 25th, 50th, and 75th percentiles as well as average consumption by household net income group and month for total consumption, social consumption, and durable consumption expenditures. We divide households according to whether they live in a three-digit postal code with an infection risk above or below the median in that month. As mentioned before, infections are typically dated at the time of their registration by a positive test.

Perhaps surprisingly, the Engel curves for total consumption are approximately constant both over time and over infection risk. If anything, there is some increase in aggregate consumption in October and November. This likely reflects national fiscal stimulus measures (see, e.g., Bachmann et al., 2021, 2022, for a discussion of the measures taken), which may have been strong enough to overcome the consumption effects of infection risk or lockdowns.[9]

[8] There are 401 counties in Germany and 671 three-digit postal regions. We match a county to each three-digit postal code based on an existing, more granular mapping between municipalities ("Gemeinden") and five-digit postal codes provided by the German *Gemeindeverzeichnis*. Municipalities are the smallest spatio-political entities in Germany, are roughly comparable in size and nested within counties. For each three-digit postal region, we mark all associated municipalities and identify the most relevant county based on the largest number of associated municipalities.

[9] These measures included a temporary reduction in the value added tax and transfers to families with children. Neither measure targeted specific regions.

Figure 2: Engel curves of consumption expenditures over time, by infection risk



Notes: Statistics on the cross-sectional distribution of expenditure on selected consumption categories by month and by net household income group and by infection risk. Social consumption is defined as spending on recreational activities outside the home, sports, tickets, restaurants, etc. Three-digit postcode areas with above (below) the median number of infections per month per 100 inhabitants are counted as high (low) risk areas. Survey weights applied.

For social consumption, we see a steady decline in spending over the three months from September to November 2020. A casual observer might interpret this decline as an indication of an effect from the increased risk of infection in October and the lockdown in November. However, the Engel curves by local infection risk, which show an almost parallel decline in consumption spending in both groups, do not permit such a conclusion. The parallel decline in consumption could be driven by seasonality, e.g., worse weather conditions making social consumption less attractive. It could also be driven by aggregate developments in the risk of infection. Finally, it could also be masking a potential reverse causality problem if places with high social consumption experience higher infection rates, which in turn are caused by high social consumption: Indeed, within a month, the red lines (indicating above-median infection risk) tend to lie above the blue lines.

For durable consumption, we see an increase in expenditures over time, in line with the findings for total consumption. However, in October (and November), unlike for total consumption, a wedge opens up between spending in high-risk and low-risk regions: Average consumption is higher in low-risk regions. The comparison between median and mean consumption shows that the differences are driven by a differential decline in particularly large expenditures. At first glance, it may be surprising to find a negative effect of infection risk on durable goods expenditures, as the relative utility of durables should increase during a pandemic with more consumption at home. However, durables must first be bought, which, at least for larger and more expensive items, often requires a visual or other physical inspection of the good, or perhaps advice from sales specialists. In short, some durables require a trip to the store, which may be onerous during a pandemic.

While these changes in the Engel curves are interesting and suggestive, they cannot conclusively answer our research question of how consumption behavior responds to infection risk. We therefore need a regression approach.

3.2 Regression results

To address the potential endogeneity problems discussed above and deal with confounding factors, we estimate the household level consumption response to local infection risk by the following regression:

$$\text{IHS}(c_{it}^u) = \beta \,\text{risk}_{it} + \tau_t + \rho_{r(it,2)} + \boldsymbol{\gamma}\boldsymbol{x}_{it} + \boldsymbol{\alpha}_t\boldsymbol{X}_{it} + e_{it}. \tag{1}$$

The (inverse hyperbolic sign transformed, $IHS(c) = \log(c + \sqrt{c^2+1})$) consumption expenditures c_{it}^u of household i at time $t \in \{\texttt{Sept}, \texttt{Oct}\}$ (or, in a robustness check, $t \in \{\texttt{Sept}, \texttt{Oct}, \texttt{Nov}\}$) for consumption category u is driven by the infection risk, risk$_{it}$, in the county the household lives in, a time fixed effect τ_t, a two-digit spatial fixed effect $\rho_{r(it,2)}$, household-level controls x_{it} (seven income category fixed effects and the number of children to account for possible effects from transfer payments targeted at families in September and October), and additional county-level controls, X_{it}, (number of hotel beds per capita as a measure of tourism intensity of a county's economy, GDP per capita, and population density).[10]

[10] Similar to infection rates, these three variables are measured at the county level. We match these variables to each household based on its 3-digit postal code, which we observe in the data using the same procedure as discussed in Footnote

By controlling for spatial fixed effects (at the level of 2-digit postal codes) and other characteristics at the finer county-level, we account for the fact that areas where households consume more (socially) tend to be more prone to infections, our main threat to identification. This fixed effects treatment is sufficient because infections in the month of consumption are, due to the incubation period, largely determined by behavior in the previous month. Our measure of risk thus exploits time series variation at the county level.

In a robustness check, we replace the combination of fixed effects at the 2-digit level and further county-level controls with a setup using only fixed effects at the 3-digit postal code level (see Footnote 8 for details on the relationship between 3-digit postal codes and counties). As a further robustness check, we measure infection risk using infections from only the first two weeks of a given month. This ensures that infections resulting from consumption decisions within the month are not included in the right-hand side of the regression. The results of all robustness checks can be found in Appendix III.

3.2.1 Social and durable consumption spending decreases when infection risks rise

In the left panel of Table 1, we present our baseline results, that is, the estimation of equation (1) with $t \in \{\texttt{Sept}, \texttt{Oct}\}$. We find a negative but insignificant effect of infection risk on total consumption expenditures. However, compared to the elasticities in macro-epidemiological models such as Eichenbaum et al. (2021, 2022b,a) or Kaplan et al. (2020), the point estimate is large: 5 percent per 100 weekly infections per hundred thousand inhabitants. Moreover, the insignificant aggregate effect masks heterogeneity across different categories of consumption. Not all consumption exposes the consumer to infection risks in the same way. Social consumption has the highest exposure and thus, in line with what has been hypothesized in the literature (Kaplan et al., 2020), is most responsive to infection risk.[11]

Also, perhaps surprisingly at first glance, spending on durable goods responds significantly. This probably reflects the fact that the purchase of durable goods is often characterized by two features: First, as described above, a shopping trip is essential for visual inspection, and second, this shopping trip can often be postponed if the durable good to be purchased is a mere replacement. In contrast, food expenditures do not respond to the risk of infection. While they may also require a trip to the store, groceries are harder to postpone, even when infections rise. We emphasize, however, that because of our short sample we can only estimate the immediate response of durable goods spending to COVID-19 infection risk. At some point, when a durable good becomes obsolete, consumers will likely go out and replace it.

8. All county-level measures are time-invariant for the frequency of our regressions. The time subscript in $\boldsymbol{X}_{it}$ simply indicates that our household sample consists of repeated cross sections.

[11] Table A.4 in Appendix II builds a bridge from Figure 2 to the results presented here for social consumption. Without any controls, there is a negative correlation between social consumption and infection risk, the time trend between September and October 2020 in the figure. Controlling for month effects, the correlation becomes positive: places with high social consumption within a month have high infection risk. In the figure, we see that the red lines are mostly above the blue lines within a month. This suggests that there is a real concern about reverse causality, which is, however, addressed in our empirical specification by including spatial fixed effects and household controls, as shown in the last two columns of Table A.4.

Table 1: Effect of local infection risk on consumption expenditures

	Sep, Oct				Sep, Oct, Nov			
	total	social	durables	groceries	total	social	durables	groceries
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Infection risk	-0.049	-0.447**	-0.279*	-0.018	-0.022	-0.417**	-0.384**	-0.028
	(0.044)	(0.195)	(0.165)	(0.053)	(0.041)	(0.183)	(0.155)	(0.052)
Infection risk (Nov)					0.008	-0.289***	-0.223**	0.044
					(0.025)	(0.097)	(0.096)	(0.035)
Household controls	YES	YES	YES	YES	YES	YES	YES	YES
Regional controls	YES	YES	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
N	7008	7008	7008	7008	10389	10389	10389	10389
R^2	0.34	0.14	0.11	0.18	0.34	0.17	0.11	0.16

Notes: OLS estimation of regressions of IHS-transformed expenditure for different consumption categories (in columns) on infection risk and controls for the September-October (September-November) sample on the left (right). Infection risk is defined as average weekly infections per thousand inhabitants in the household's county of residence. Because consumption data pertains to a full month, we estimate regressions with total monthly infections scaled by 7/30 to obtain average weekly infections in that month. Household controls include seven income category fixed effects and the number of children. County-level controls include GDP per capita, the number of hotel beds per capita, and population density. Spatial fixed effects at the 2-digit postal code level. The regressions use survey weights. Robust standard errors in parentheses. $^{***}\, p < 0.01$, $^{**}\, p < 0.05$, $^{*}\, p < 0.10$. The estimated coefficients for all controls can be found in Table A.5.

The effects on social and durable consumption expenditures are also economically significant. An additional one hundred infections per one hundred thousand inhabitants per week leads to a 0.45 log point (-36 percent) decrease in social consumption expenditures and a 0.28 log point (-24 percent) decrease in expenditures on consumer durables.[12] We can gauge the magnitude of these effect sizes both through the time-series dimension of infections and through a cross-sectional perspective. Infections went up by about fifty cases per one hundred thousand inhabitants per week between September and October (see Figure 1), implying that the expected consumption decline is about half of the numbers above. Fifty cases per hundred thousand is also roughly the difference between the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of the infection risk distribution across counties in October, see again Figure 1.

How do the estimates in Table 1 fit together? Assuming a zero response in spending on groceries, we can use the estimated responses together with data on average consumption spending in September 2020 and the national average increase in COVID-19 risk between September and October 2020 to calculate that the average household reduced its total consumption spending by €54, its social consumption spending by €22, and its spending on durable goods by €121. This suggests that households must have increased their spending on other consumption categories, that were not explicitly asked about

[12] Are the effects of infection rates nonlinear? We tested polynomials of infection risk as well as specifications using a variety of indicators for different ranges of infection risk. None of these specifications rejected the null hypothesis of linearity. Importantly, we found no evidence of convex effects.

in the survey, such as streaming subscriptions, books, video games, etc., by about €90, a reasonable amount.

Relatedly, we can also use our estimates to compute counterfactual scenarios, given the response of households in October 2020. In Germany, at the peak of the pandemic in 2022, after the vaccination campaign had largely allowed a return to pre-pandemic rules and behaviors, infections reached rates of 750 or 1200 per hundred thousand inhabitants per week. Our estimates imply that at these infection levels, consumption would have collapsed almost completely (more than -95 percent for social consumption) if the perceived health risks, e.g., due to the vaccines, had not changed. This underscores the enormous economic value of vaccines.

Similarly, given the (comparatively lower, but still large) number of infections in November 2020, on average 150 per hundred thousand inhabitants, the predicted drop in social consumption (relative to no infections) for November is large even without any lockdown measures. It would have been approximately 0.68 log points (-49%). This compares well with the actual decline between September and November, implying that the lockdown measures likely had little to no additional impact on social consumption.

For durable goods, the estimates predict a decline of 0.42 log points (-34%) in November. This is not the same as the actual aggregate change in durable goods purchases for the month. If anything, we see an increase in purchases relative to September, albeit, in line with the regression results, mainly in low-risk areas; see Figure 2. However, this is not a contradiction: the observed evolution of durable consumption was positively affected by the temporary cut in the VAT (Bachmann, Born, Goldfayn-Frank, Kocharkov, Luetticke, and Weber, 2023a,b); also, the hygiene measures imposed on shopping venues in November can be expected to have had a positive effect, according to our estimates. If households care systematically and as much about the risk of infection as we estimate, measures that improve hygiene in shopping centers, such as requiring people to wear masks or limiting the number of people shopping per square meter, can have a positive effect on durable spending by reducing the (perceived) risk of infection. This again shows that lockdown measures do not necessarily lead to excessive economic losses if they are combined with smart hygiene plans and perhaps fiscal stimulus measures.

The right panel of Table 1 shows estimates that include data from November ($t \in \{\texttt{Sept}, \texttt{Oct}, \texttt{Nov}\}$), the month in which the consumption lockdown measures began, and estimates a separate risk effect for that month. This serves two purposes: First, it increases the estimation precision of the controls, and second, the estimated effect for November provides a quasi-placebo test, as one would expect the impact of infection risk on consumption decisions to be muted during consumption lockdowns. Indeed, the estimated effects of infection risk in the pre-lockdown months of September and October remain very similar, with a slightly stronger effect on durable spending. The estimated infection risk effects in November are smaller but still statistically significant for social consumption and consumer durables.

3.2.2 Robustness checks

Our baseline estimates could suffer from a (downward) bias because some households spend nothing on a particular consumption category in a given month.This is a potential concern not only for durables, where about nine percent of households in our sample report zero spending, but also for social consumption, where as many as a third report spending nothing. Reassuringly, our results are robust to estimating a Tobit model that allows for censoring at zero, see Appendix III Table A.6. Consistent with the notion that censoring introduces a bias toward zero, we actually find slightly larger point estimates for durable and social spending.

In our baseline specification of Table 1, infection risk is measured based on reported cases within the county of residence. However, the places where households shop are not necessarily in their county of residence. Therefore, households can be expected to respond to infection risk beyond their county of residence. In particular, this is likely to be the case for purchases of larger durable goods. We therefore repeat our estimation using an alternative measure of infection risk, calculated as the infection risk in a 30 km radius around the home county,[13] and present the results in Appendix III Table A.7. We find qualitatively similar negative effects of infection risk on consumption expenditures. For social and durable consumption, the effects are quantitatively even stronger. As expected, this is especially true for durable goods.

The hypothesis that the risk of infection could change households' consumption expenditure is based on the fact that most consumption involves social contact. However, this very fact could generate a force of reverse causality: *Exogenous* shifts in consumption could increase infections, introducing a positive correlation between consumption and infection and thus potentially biasing our estimates downward.[14] To gauge the magnitude of such a potential bias, we take advantage of the virus's incubation period of one to two weeks:[15] Exogenous consumption shocks can, by-and-large, only generate additional COVID-19 infections in the same month if they lead to consumption in the first half of the months which would then lead to infections registered in the second half of said month. Hence, infections registered and reported during the first two weeks of a month should be mostly unaffected by such shocks and thus largely exogenous to households' consumption choices within the month. Appendix III

[13] For each county, we add to its monthly infections the infections from other counties whose centroids fall within the 30-km radius around its centroid. We repeat the same procedure for the population and divide the total number of infections by the total population. We compute this spatially broader measure of infection risk for each county and each month, and match the data to household survey information at the 3-digit postal code level, following the procedure previously described in Footnote 8.

[14] As we have argued, this logic also applies to persistent level differences across regions, necessitating our empirical approach that accounts for spatial fixed effects. However, our estimates may still suffer from a bias introduced by transitory consumption shocks.

[15] McAloon et al. (2020) find, for the variant of the Corona virus circulating in the fall of 2020, an average incubation period of 6 days and a 95th percentile of 12 days. This is also the information that the *Robert-Koch-Institut* provides on its website: `https://www.rki.de/DE/Content/InfAZ/N/Neuartiges_Coronavirus/Steckbrief.html`.For the time of our analysis the wild-type was still the dominant strain. We further note that, since the incubation period is the time interval between infection and first symptoms, for our purposes we have to add the time between first symptoms and the taking of the test to these numbers. This was typically another couple of days.

Table A.8 reports estimates based on infection risk measured using only infections during the first two weeks of a month (divided by two to obtain weekly averages to facilitate comparison of coefficients across specifications). In fact, the point estimates increase substantially, which indicates that reverse causality possibly makes our baseline estimate indeed somewhat conservative.[16] However, using only the infections in the first two weeks, the precision of the estimates declines, presumably because our measure no longer captures all relevant infections.

As a final robustness check, we use more fine-grained spatial fixed effects. Spatial fixed effects are key to our identification because they filter out persistent consumption and infection differences across regions, for example due to regional differences in the relative size of sectors, such as retail, that are particularly affected by COVID-19 infections, which could confound estimates of risk sensitivity. Due to sample size constraints, our baseline estimation controls for 2-digit zip code-level fixed effects—of which there are 95—rather than county-level fixed effects—of which there are 401. We present the results of a robustness check using the full set of county-level fixed effects in Appendix III Table A.9. The results are virtually unchanged.

3.2.3 Why does consumption decrease?

So far, we have only established that expenditures on social consumption and durable goods decreased with higher infection risk. This could be due to a number of different channels: Fear of infection and the associated risk of morbidity and mortality, pro-social behavior in the face of the risk of infecting others, or simply the expectation of a negative economic fallout from the local evolution of the pandemic.

The left panel of Table 2 shows that controlling for income and income risk expectations has little influence on the relationship between consumption and infection risk. This suggests that the consumption responses documented in Table 1 are not driven by the expected economic impact of the pandemic. This is also consistent with the statistically insignificant effect of infection risk on total consumption.

Regarding the role of pro-social behavior, Bartscher, Seitz, Siegloch, Slotwinski, and Wehrhöfer (2021) argue that voter turnout in European Union (EU) parliamentary elections is a good proxy for social capital. The idea, going back to Putnam (1993), is that participation in an election is a sign of a particular sense of civic responsibility, and arguably particularly so in EU elections, where the powers of the parliament are relatively limited and the weight of a single vote is particularly low. We classify a county as having low social capital if the participation rate of its federal state was below the median in 2019. The right panel of Table 2 shows that in counties with low social capital, households cut back on social consumption spending much less when the risk of infection increases. This is consistent with the view that the reduction in consumption in response to infection risk is partly driven by pro-social behavior.[17]

Finally, to gauge the role of self-interest in the documented consumption restraint, we exploit the fact

[16] In particular, this also rules out the possibility that weather conditions drive our estimates of the infection-consumption nexus. Weather conditions in a month may drive consumption in that month, but they cannot affect recorded infections in the first two weeks. These result from exposure in the previous month.

[17] We note that our interacted results with social capital could also reflect a better information flow among a region's population with higher social capital, rather than pro-social preferences per se.

Table 2: Splitting regions by social capital / Controlling for income (risk) expectations

	Controlling for income (risk) expectations				Regional heterogeneity by social capital			
	total	social	durables	groceries	total	social	durables	groceries
	(5)	(6)	(7)	(8)	(1)	(2)	(3)	(4)
Infection risk	-0.048	-0.436**	-0.277*	-0.020	-0.013	-0.722***	-0.256	0.066
	(0.044)	(0.192)	(0.164)	(0.053)	(0.048)	(0.217)	(0.187)	(0.061)
Infection risk ×					-0.063	0.489**	-0.044	-0.146**
low social capital					(0.048)	(0.201)	(0.177)	(0.059)
Income (risk) expectations	YES	YES	YES	YES	NO	NO	NO	NO
Household controls	YES	YES	YES	YES	YES	YES	YES	YES
Regional controls	YES	YES	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
N	7008	7008	7008	7008	7008	7008	7008	7008
R^2	0.34	0.17	0.12	0.18	0.34	0.15	0.11	0.18

Notes: Left panel: Adding quantitative income and income risk expectations from a probabilistic twelve-months-ahead income growth question, see Chapter 4 in Bachmann et al. (2021) for details. Right panel: Adding a binary indicator for low social capital and its interaction with infection risk. Social capital is proxied by the participation rate in the last elections for the EU parliament at the Bundesland (state) level (Bartscher, Seitz, Siegloch, Slotwinski, and Wehrhöfer, 2021). Households are categorized as living in a "low social capital" environment if their state participation rate was below median. Both: Otherwise identical to baseline specification, see notes of Table 1. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

that a key feature of the COVID-19 disease was a steep gradient of severity and mortality in age. For people under the age of 40, infections in most cases had relatively mild consequences (Gallo Marin et al., 2021). This fact was already well-known by fall 2020. One would therefore expect a much greater sensitivity of consumption patterns to the risk of infection for the elderly. To test this hypothesis, we split the sample along the median age of household heads, which is 40 in our dataset, and estimate two separate sensitivity parameters for each consumption category.[18] Table 3 shows the results for both social and durable consumption expenditures. Columns one and four repeat the baseline results. Columns two and five split the sensitivity to infection by age.

Indeed, we find that only the older cohorts' response to infection risk is statistically significant and about twice as large as that of the younger cohorts. The difference in sensitivities is particularly strong for social consumption. Nevertheless, we also find a sizeable negative, albeit insignificant, sensitivity to infection risk for the young. Compared to the inclusion of social capital measures, allowing for age

[18] We also tested for effect heterogeneity by household composition, allowing for the effect of infection risk to differ between households with and without children and by household size to investigate potentially differentially pro-social behavior within families. We did not find any statistically significant differences, nor did the point estimates suggest a clear pattern. It is also important to note that the survey was conducted online, so we can assume that the old and young households in our survey had similar opportunities to shift their spending on durable goods online. This means that any differential behavior we find between young and old households is likely driven by their intended shopping behavior to avoid mortality/morbidity risk, not by differences in shopping opportunities.

Table 3: Social and durable consumption spending, heterogeneity by age

	durables (1)	durables (2)	durables (3)	social (4)	social (5)	social (6)
Infection risk	-0.279*			-0.447**		
	(0.165)			(0.195)		
Infection risk, young		-0.161			-0.194	
		(0.189)			(0.221)	
Infection risk, old		-0.287*			-0.496**	
		(0.172)			(0.196)	
Infection risk, young × poor			-0.165			-0.164
			(0.217)			(0.249)
Infection risk, young × rich			-0.302			-0.046
			(0.248)			(0.307)
Infection risk, old × poor			-0.444**			-0.160
			(0.191)			(0.218)
Infection risk, old × rich			-0.229			-0.677***
			(0.239)			(0.260)
Household controls	YES	YES	YES	YES	YES	YES
Regional controls	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES	YES	YES
N	7008	7008	6053	7008	7008	6053
R^2	0.11	0.13	0.14	0.14	0.17	0.19

Notes: Regressions including, in addition to the baseline controls, an additional control for household age and its interaction with infection risk. Households are classified as "old" if the main earner is over 40. Households are classified as "rich" if their net wealth exceeds 50,000 Euros. Otherwise identical to the baseline specification, see notes of Table 1. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

heterogeneity in the effect of infection risks increases the statistical explanatory power of the regression more strongly.

Expenditures on both consumer durables and social consumption increase with income and wealth (see Table A.3 in Appendix II), which tend to increase with age. Thus, the sensitivity to infection risk may be lower for the young for the mechanical reason that they spend less on both categories of consumption. To test this, we add an additional interaction with household wealth, split at 50,000 Euros, roughly the median in our data. Columns three and six of Table 3 show the estimated risk sensitivities for each subsample. Reassuringly, the effects are still concentrated in the older cohorts. In particular, we find interesting heterogeneity within the old: It is the old wealth-poor who respond most strongly in their durable consumption expenditures, while it is the old wealth-rich who respond most strongly in their social consumption expenditures. This pattern reflects the relative levels of consumption expenditure shares in September 2020; see Table A.3 in Appendix II. The old wealth-poor spend particularly little on social consumption, which is likely to be a luxury for them (4 percent of their income compared to 7 percent for the wealth-rich), and the old wealth-rich spend little on durable goods (18 percent of their income compared to 20 percent for the wealth-poor); they presumably already own most of the consumer durables they need. It is for these different categories of consumption, social and consumer durables, that the respective household types have less room for maneuver to reduce spending in the first place.

3.2.4 Durable consumption expenditures

As we have shown in the previous sections, there is a statistically and economically significant negative effect of the risk of infection on spending on durable goods. Durable goods expenditures in the survey are the sum of expenditures on vehicles, home appliances and furniture, clothing, and one "other"-category. Therefore, we re-estimate equation (1) with consumption expenditures for subcategories of durable goods. In addition, to obtain a decomposition of the total effect, we also estimate a specification where we use expenditures relative to household net income as the left-hand side variable.

Table 4: Effect of infection risk on durable goods expenditures, IHS and as a share of income

	IHS-transformed expenditures				expenditures as share of income			
	durables (1)	home (2)	apparel (3)	vehicles (4)	durables (5)	home (6)	apparel (7)	vehicles (8)
Infection risk	-0.279*	-0.300	-0.338*	-0.036	-0.077**	-0.024*	-0.006*	-0.043
	(0.165)	(0.231)	(0.194)	(0.112)	(0.038)	(0.014)	(0.003)	(0.034)
Household controls	YES	YES	YES	YES	YES	YES	YES	YES
Regional controls	YES	YES	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
N	7008	7008	7008	7008	7008	7008	7008	7008
R^2	0.11	0.06	0.11	0.04	0.03	0.02	0.05	0.03

Notes: Regressions of consumption expenditures as a share of household net income for each durable consumption category for the September-October sample (right-hand panel). Otherwise identical to the baseline specification, see notes of Table 1. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4 shows the results. The first column repeats the baseline results presented earlier for expenditures on consumer durables. Columns two to four report expenditure sensitivities for subcategories, which are very similar to the aggregate sensitivity, except for virtually no response for vehicle purchases. Columns five to eight show results for consumption expenditures as a share of household income.

Again, in this specification, the risk of infection has a negative effect on durable goods expenditures. One hundred more local infections per hundred thousand inhabitants per week reduce the expenditure share on durables by 7.7 percentage points. The largest contribution comes from the purchase

Table 5: Quantile effects of county of residence infection risk on durable goods shares

	OLS (1)	Q50 (2)	Q75 (3)	Q90 (4)	Q95 (5)
			durables		
Infection risk	-0.077**	-0.007	-0.050***	-0.100**	-0.172**
	(0.038)	(0.006)	(0.019)	(0.048)	(0.078)
			home appliances and furniture		
Infection risk	-0.024*	0.000	-0.011	-0.086***	-0.088**
	(0.014)	(0.014)	(0.010)	(0.020)	(0.037)
			apparel		
Infection risk	-0.006*	-0.001	-0.004	-0.009	-0.018**
	(0.003)	(0.003)	(0.004)	(0.006)	(0.008)
N	7008	7008	7008	7008	7008

Notes: Quantile regressions of consumption expenditures as a share of household net income for durable consumption categories. Estimates at the 50th, 75th, 90th and 95th percentiles for the September-October sample. Otherwise identical to the baseline specification, see notes of Table 1. Robust standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

of vehicles, although it is not statistically significant because such purchases are rare, see Table A.3 in Appendix II. The next two categories are appliances/furniture and clothing, where the risk of infection does have an economically and statistically significant negative effect; together they account for just over a third of the total effect.

In Table 5 we use quantile regressions to examine where in the distribution the effects for spending on consumer durables are coming from. The distribution of spending on consumer durables is of course largely driven by incomes. Therefore, we focus on spending shares instead to investigate whether the consumption restraint in spending on consumer durables comes from households that spend little relative to their income or households that spend a lot. One would expect households to cut back especially on rare but large durable purchases that require more in-depth inspection and/or advice from sales professionals, and thus social interaction with a potential for exposure to infection. The results in Table 5 confirm this conjecture, both for durable goods expenditures as a whole (see also the lowest panel in Figure 2) and for the subcategories of appliances/furniture and clothing.[19]

[19] The large share of households (94.5 percent) that did not purchase any vehicles makes a quantile regression for vehicles infeasible.

4 Conclusion

In this paper, we investigate how local COVID-19 infection risk affected consumption expenditures—in the absence of lockdown measures and before vaccines were available. We use a high-quality household consumption survey designed by the German Federal Statistical Office to track micro-level consumption dynamics during the pandemic.

We use within-county variation in infection risk to identify households' consumption response to infection risk and find that it leads to a decline in consumption spending. While the effect is substantial, it is not statistically significant for total consumption. For social consumption and spending on durable goods, the effect is both economically and statistically significant and much larger than what many macroeconomic models of the pandemic are calibrated to. Households reduced consumption to avoid exposure to the virus, to avoid infection. This interpretation is supported by the fact that the reduction in consumption was particularly large among the elderly. There is also evidence consistent with pro-social motives behind households' consumption restraint. We find no evidence that the decline in consumption is due to the expected economic fallout of the pandemic itself.

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APPENDIX

I Further information on the data

Table A.1: Consumption survey sample size

survey wave	total	with weights
July	4416	4251
August	4418	4233
September	4369	4164
October	4419	4218
November	4364	4154
All months	21986	21020

Notes: Survey weights have been calculated by the data provider based on household income, amongst other characteristics. The few households that did not supply the necessary information were excluded from weight calculations. We drop households without survey weights.

Table A.2: Sample selection steps

Restriction	Gesamt	Sep	Oct	Nov
With survey weights, in months Sep, Oct and Nov	12535	4164	4217	4154
Data cleaning following Bachmann et al. (2021)	11286	3762	3837	3687
With data on consumption, income, children	11286	3762	3837	3687
With data on regional identifiers	10389	**3467**	**3541**	3381

Notes: Bold entries sum to 7008, the core baseline sample.

II Descriptive statistics and more detailed regression tables

Table A.3: Summary statistics on consumption expenditures by category and sample

	total	social	groceries	durables			
				total	home	apparel	vehicles
IHS-transformed expenditures, mean	7.88	3.50	6.27	5.36	2.63	3.52	0.39
Expenditures as share of income, mean	0.69	0.05	0.14	0.21	0.09	0.04	0.08
Expenditures as share of income, median	0.57	0.02	0.12	0.06	0.00	0.03	0.00
Expenditures as share of income, 75th percentile	0.83	0.05	0.19	0.17	0.08	0.06	0.00
Expenditures as share of income, 90th percentile	1.08	0.13	0.25	0.38	0.25	0.09	0.00
Expenditures as share of income, 95th percentile	1.29	0.23	0.31	0.64	0.39	0.13	0.00
Household main earner younger than 40							
Mean, IHS-transformed expenditures	7.87	4.27	6.15	5.75	3.29	3.85	0.57
Mean, expenditures as share of income	0.72	0.07	0.13	0.26	0.11	0.04	0.10
Household main earner aged 40 or older							
Mean, IHS-transformed expenditures	7.87	3.51	6.29	5.13	2.24	3.37	0.22
Mean, expenditures as share of income	0.67	0.05	0.14	0.18	0.08	0.04	0.06
Household main earner younger than 40, household wealth below 50.000 Euro							
Mean, IHS-transformed expenditures	7.71	4.04	6.08	5.48	3.09	3.75	0.44
Mean, expenditures as share of income	0.71	0.07	0.14	0.22	0.09	0.05	0.07
Household main earner younger than 40, household wealth at least 50.000 Euro							
Mean, IHS-transformed expenditures	8.25	5.10	6.35	6.49	4.26	4.18	0.95
Mean, expenditures as share of income	0.76	0.08	0.10	0.38	0.16	0.04	0.16
Household main earner aged 40 or older, household wealth below 50.000 Euro							
Mean, IHS-transformed expenditures	7.69	2.88	6.17	4.96	2.11	3.05	0.26
Mean, expenditures as share of income	0.74	0.04	0.16	0.20	0.07	0.04	0.08
Household main earner aged 40 or older, household wealth at least 50.000 Euro							
Mean, IHS-transformed expenditures	8.14	4.47	6.49	5.43	2.51	3.80	0.21
Mean, expenditures as share of income	0.61	0.07	0.11	0.18	0.09	0.03	0.05

Notes: Statistics for IHS-transformed expenditures and expenditures relative to net household income for each consumption category. The top panel shows statistics for the main estimation sample, that is all households for the months September and October 2020, to benchmark our estimates. The panels below the top panel show heterogeneity across age-wealth sub-samples for September 2020, because we use them to interpret our results in Table 3 in the main text and thus need them to be free from the impact of the second wave of infections hitting October 2020. All statistics weighted by survey weights.

Table A.4: Social consumption effect across specifications

	Social consumption			
	plain	month FE	region controls	baseline
Infection risk	-0.379***	0.320**	-0.149	-0.447**
	(0.087)	(0.137)	(0.180)	(0.195)
Household controls				YES
Regional controls			YES	YES
Region fixed effects			YES	YES
Month fixed effects		YES	YES	YES
N	7536	7536	7536	7008
R^2	0.00	0.01	0.04	0.18

Notes: OLS estimation of regressions of IHS-transformed expenditure for social consumption on infection risk with varying control vectors for the September-October sample. Infection risk is defined as average weekly infections per thousand inhabitants in the household's county of residence. Because consumption data pertains to a full month, we estimate regressions with total monthly infections scaled by $7/30$. Household controls include seven income category fixed effects and the number of children. Regional controls include GDP per capita, the number of hotel beds per capita, and population density. Regional fixed effects at the 2-digit postal code level. The regressions use survey weights. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.5: Baseline estimation showing all coefficients

	Sep, Oct					Sep, Oct, Nov			
	total	social	durables	groceries		total	social	durables	groceries
Infection risk	-0.049	-0.447**	-0.279*	-0.018		-0.022	-0.417**	-0.384**	-0.028
	(0.044)	(0.195)	(0.165)	(0.053)		(0.041)	(0.183)	(0.155)	(0.052)
Infection risk (Nov)						0.018	-0.673***	-0.520**	0.103
						(0.059)	(0.226)	(0.224)	(0.081)
October	0.008	-1.707***	-0.415	0.249		-0.007	-1.721***	-0.347	0.272
	(0.157)	(0.632)	(0.547)	(0.185)		(0.157)	(0.637)	(0.545)	(0.186)
November						-0.010	-0.759	0.088	-0.032
						(0.159)	(0.632)	(0.596)	(0.199)
Income 1100-1499 EUR	0.403***	0.442***	0.588***	0.363***		0.362***	0.373***	0.580***	0.283***
	(0.035)	(0.147)	(0.130)	(0.050)		(0.029)	(0.117)	(0.108)	(0.046)
Income 1500-1999 EUR	0.613***	1.078***	0.912***	0.467***		0.588***	0.870***	0.923***	0.431***
	(0.036)	(0.143)	(0.129)	(0.052)		(0.029)	(0.113)	(0.106)	(0.044)
Income 2000-2599 EUR	0.763***	1.504***	1.113***	0.571***		0.764***	1.220***	1.153***	0.567***
	(0.034)	(0.132)	(0.122)	(0.048)		(0.027)	(0.108)	(0.102)	(0.042)
Income 2600-3599 EUR	0.983***	1.856***	1.419***	0.772***		0.938***	1.469***	1.433***	0.731***
	(0.032)	(0.126)	(0.113)	(0.046)		(0.027)	(0.103)	(0.095)	(0.040)
Income 3600-4999 EUR	1.200***	2.204***	1.712***	0.899***		1.147***	1.781***	1.756***	0.883***
	(0.034)	(0.129)	(0.117)	(0.047)		(0.028)	(0.106)	(0.098)	(0.040)
Income 5000 EUR and more	1.403***	2.677***	2.063***	1.062***		1.401***	2.186***	2.129***	1.027***
	(0.040)	(0.152)	(0.135)	(0.050)		(0.034)	(0.125)	(0.113)	(0.044)
Number of children	0.077***	0.217***	0.344***	0.135***		0.088***	0.299***	0.385***	0.132***
	(0.011)	(0.047)	(0.041)	(0.014)		(0.009)	(0.041)	(0.032)	(0.012)
1000 inhabitants per km^2	0.025	0.114	0.057	-0.042*		0.029*	0.073	0.025	-0.046**
	(0.019)	(0.077)	(0.070)	(0.022)		(0.018)	(0.071)	(0.064)	(0.021)
GDP p.c., thounsands	0.014*	-0.007	-0.018	-0.006		0.011	-0.033	-0.040	-0.005
	(0.008)	(0.031)	(0.028)	(0.009)		(0.007)	(0.028)	(0.025)	(0.009)
Beds p.c.	-0.058	0.649	1.312*	0.483**		-0.155	0.793	0.940	0.540***
	(0.231)	(0.811)	(0.703)	(0.187)		(0.220)	(0.756)	(0.669)	(0.187)
Oct $\times$ pop. density	0.026	0.164*	0.084	0.035		0.023	0.161*	0.098	0.034
	(0.021)	(0.085)	(0.073)	(0.026)		(0.021)	(0.085)	(0.072)	(0.026)
Oct $\times$ GDP p.c.	0.001	0.059**	0.025	-0.009		0.001	0.059**	0.024	-0.010
	(0.007)	(0.027)	(0.023)	(0.008)		(0.007)	(0.027)	(0.023)	(0.008)
Oct $\times$ beds p.c.	0.314	-1.287	0.364	-0.435*		0.352	-1.243	0.338	-0.460*
	(0.341)	(1.061)	(0.858)	(0.235)		(0.349)	(1.056)	(0.863)	(0.236)
Nov $\times$ pop. density						0.013	0.003	0.014	0.010
						(0.021)	(0.083)	(0.077)	(0.027)
Nov $\times$ GDP p.c.						-0.001	-0.026	0.012	-0.001
						(0.007)	(0.027)	(0.026)	(0.009)
Nov $\times$ beds p.c.						0.039	-1.281	-1.124	-0.246
						0.255	0.939	0.813	0.222
Region fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	7008	7008	7008	7008		10389	10389	10389	10389
R^2	0.34	0.14	0.11	0.18		0.34	0.17	0.11	0.16

Notes: OLS estimation of regressions of IHS-transformed expenditure for different consumption categories (in columns) on infection risk and controls for the September-October (September-November) sample on the left (right). Infection risk is defined as average weekly infections per thousand inhabitants in the household's county of residence. Because consumption data pertains to a full month, we estimate regressions with total monthly infections scaled by $7/30$. Household controls include seven income category fixed effects and the number of children. Regional controls include GDP per capita, the number of hotel beds per capita, and population density. Regional fixed effects at the 2-digit postal code level. The regressions use survey weights. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

III Robustness

Table A.6: Tobit model

	Sep, Oct				Sep, Oct, Nov			
	total	social	durables	groceries	total	social	durables	groceries
Infection risk	-0.049	-0.604*	-0.308*	-0.018	-0.022	-0.600*	-0.422**	-0.028
	(0.043)	(0.311)	(0.181)	(0.053)	(0.041)	(0.318)	(0.171)	(0.052)
Infection risk (Nov)					0.008	-0.553***	-0.258**	0.045
					(0.025)	(0.208)	(0.108)	(0.035)
Household controls	YES	YES	YES	YES	YES	YES	YES	YES
Regional controls	YES	YES	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
N	7008	7008	7008	7008	10389	10389	10389	10389
R^2 (pseudo)	0.18	0.03	0.02	0.08	0.18	0.04	0.02	0.06

Notes: Estimates obtained from a Tobit model with a cut-off at zero, using the baseline specification, see notes of Table 1, or Table A.5. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.7: Effect of infection risk within a 30km radius on consumption expenditures

	Sep, Oct				Sep, Oct, Nov			
	total	social	durables	groceries	total	social	durables	groceries
Infection risk	-0.056	-0.555**	-0.467**	-0.077	-0.029	-0.496**	-0.539***	-0.070
	(0.058)	(0.240)	(0.209)	(0.070)	(0.053)	(0.224)	(0.193)	(0.066)
Infection risk (Nov)					-0.009	-0.325***	-0.252**	0.078*
					(0.031)	(0.120)	(0.116)	(0.041)
Household controls	YES	YES	YES	YES	YES	YES	YES	YES
Regional controls	YES	YES	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
N	7008	7008	7008	7008	10389	10389	10389	10389
R^2	0.34	0.14	0.11	0.18	0.34	0.17	0.11	0.16

Notes: Regression estimates with infection risk measured as infections relative to population in a 30km radius around the household's county of residence. Otherwise identical to baseline specification, see notes of Table 1. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.8: Measuring risk only during two initial weeks of month

	Sep, Oct				Sep, Oct, Nov			
	total	social	durables	groceries	total	social	durables	groceries
Infection risk	-0.059	-0.564*	-0.509*	-0.108	-0.019	-0.752***	-0.712***	-0.031
	(0.074)	(0.312)	(0.278)	(0.085)	(0.065)	(0.267)	(0.239)	(0.077)
Infection risk (Nov)					0.009	-0.188**	-0.201***	-0.001
					(0.019)	(0.075)	(0.069)	(0.023)
Household controls	YES	YES	YES	YES	YES	YES	YES	YES
Regional controls	YES	YES	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
N	7008	7008	7008	7008	10388	10388	10388	10388
R^2	0.34	0.14	0.11	0.18	0.34	0.17	0.11	0.16

Notes: Regression estimates with infection risk measured as infections during the first two weeks (divided by two to obtain weekly averages) per thousand inhabitants in the household's county of residence. Otherwise identical to baseline specification, see notes of Table 1, or Table A.5. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.9: Fixed effects at the county (Kreis) level

	Sep, Oct				Sep, Oct, Nov			
	total	social	durables	groceries	total	social	durables	groceries
Infection risk	-0.028	-0.479*	-0.443**	0.036	-0.025	-0.498**	-0.507***	-0.048
	(0.061)	(0.247)	(0.211)	(0.071)	(0.050)	(0.213)	(0.185)	(0.062)
Infection risk (Nov)					0.002	-0.371***	-0.230**	0.049
					(0.027)	(0.108)	(0.105)	(0.038)
Household controls	YES	YES	YES	YES	YES	YES	YES	YES
Regional controls	YES	YES	YES	YES	YES	YES	YES	YES
Region fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
N	7008	7008	7008	7008	10389	10389	10389	10389
R^2 (pseudo)	0.38	0.18	0.16	0.22	0.36	0.18	0.14	0.06

Notes: OLS regressions with county-level fixed effects (replacing the spatially coarser fixed effects at the 2-digit postal code level). Otherwise identical to baseline specification, see notes of Table 1, or Table A.5. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

IV Survey questions

We translate the survey questions underlying our household-level data.

Questions on consumption

- Please provide an estimate of how much money your household spent overall during the last month (September)? Please consider ALL expenditures of ALL household members. Relevant expenditures include, for example, rent, insurance policies, transportation, telecommunication, food, drinks and tobacco, goods for everyday use, subscriptions. We do NOT mean: repayments of debt and credit or savings. (Answer in euros)
- Please provide an estimate of how much money your household spent on durable consumption goods during the last month (September)? (Answer in euros)

  a) Vehicles (e.g., cars, bicycles, motorcycle)

  b) Furnishings and home wares (e.g., furniture, lights, carpets, tableware)

  c) Appliances (e.g., TV sets, mobile phones, refrigerator, drilling machine, laptop)

  d) Apparel and footwear

  e) Miscellaneous
- Please provide an estimate of how much money your household spent during the last month (September) on entrance fees and services outside the home in the areas of leisure, culture and sports, dining-out, and vacation? (Answer in euros)
- Please provide an estimate of how much money your household spent during the last month (September) on food, drinks and tobacco products? We mean products that are consumed at home, including deliveries of food and drinks. (Answer in euros)

Other questions

- The household net income is the sum of net incomes of ALL household members. Please consider in particular: wages/salaries, income from self-employment, pensions, Christmas bonus, 13./14. monthly salary, vacation bonuses, income from lease and rentals, capital income (interest, dividends), alimony payments, child benefits, public transfers (rent allowances, parental allowances), education assistance, unemployment benefits, scholarships, one-time payments (indemnity or bonus payments), income from secondary employment. How large was the net income of your household during the last month (September) in total?

  a) below 1,100 Euro

  b) 1,100 up until 1,500 Euro

c) 1,500 up until 2,000 Euro
d) 2,000 up until 2,600 Euro
e) 2,600 up until 3,600 Euro
f) 2,600 up until 5,000 Euro
g) 5,000 Euro or above
h) Prefer not to answer

- How high do you estimate total household wealth to be? Wealth includes, for example, real estate, bank deposits, stocks, term deposits and objects of value. Subtract all debts and liabilities of your household. Debts and liabilities include, for example, mortgages, consumer loans and student loans.

  a) Below 0 Euro
  b) 0 up until 2,000 Euro
  c) 2,000 up until 50,000 Euro
  d) 50,000 up until 220,000 Euro
  e) 220,000 up until 270,000 Euro
  f) 270,000 up until 450,000 Euro
  g) 450,000 or above
  h) Do not know
  i) Prefer not to answer

- What is the postal code of your place of residence? In case of multiple residences, please refer to the main residence. (5-digit answer; however, trimmed to three digits by data provider to prevent identification of survey respondents)
- In which year was the household's main earner born? (4-digit answer)
- How many unmarried children belong to your household?