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Pandemic Consumption

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Pandemic Consumption*

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Abstract

This paper examines how households adjusted their consumption behavior in response to COVID-19 infection risk during the early phase of the pandemic. 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 durables and social activities by, respectively, 24 percent and 36 percent in response to one hundred extra 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

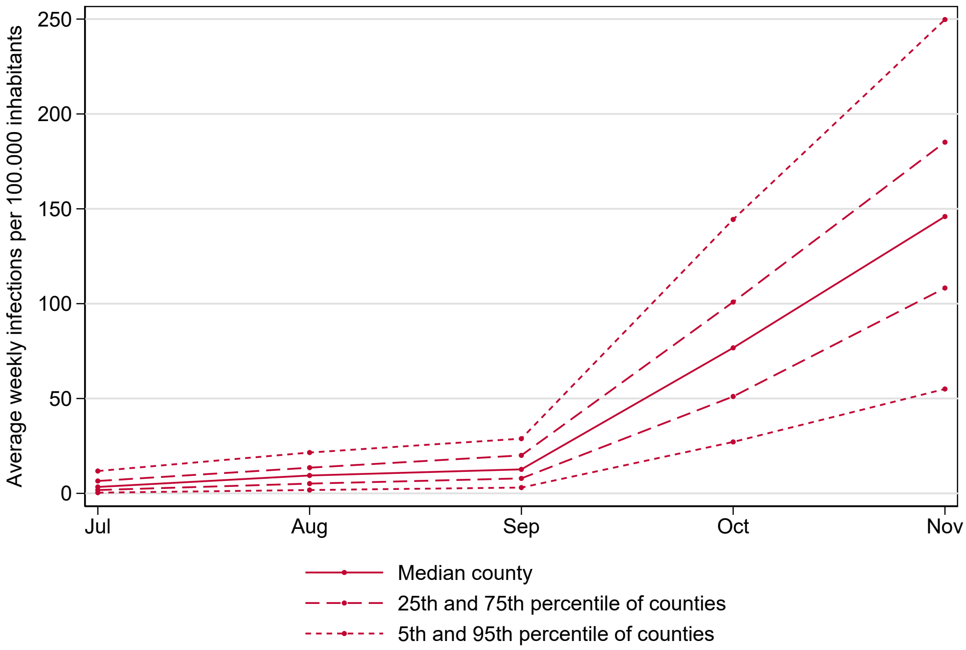
In 2020, the COVID-19 pandemic spread around the world with disastrous economic consequences. To safeguard public health, many governments decided to restrict not only production but also sales and consumption activities. These measures were controversial, because, ultimately, governments faced a trade-off between the level of economic activity and the health ramifications of COVID-19 infections. One central question of the debate was how and which households would react without government interventions to infection risks. Would all households curb consumption anyway to protect themselves and others voluntarily, or would only the most vulnerable households decrease their consumption? Those that opposed non-pharmaceutical public health measures argued that people would protect themselves optimally against COVID-19 infections. Therefore, government interventions would lead to an excess loss of economic activity. Those in favor of the public health measures emphasized the following consumption-infection externality: consumption that involves human interaction leads to more infections, which further increases the infection risk for everybody, and thus leads to higher mortality among vulnerable segments of the population. In this case, a lack of government intervention could lead to an excess loss of economic activity: in the laissez-faire equilibrium, infections would quickly rise, leading to an even stronger consumption restraint at least amongst the vulnerable segment of the population. Economists have informed this debate based on 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). Missing at the time and still missing are reliable estimates of the laissez-faire consumption response of households to COVID-19 infection risk, that is, their response absent 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 decrease their spending on social or leisure consumption (leisure outside the home, sports, tickets, restaurants etc.) and on durable consumer goods when local infection risks are larger. An increase of the weekly infection risk by one hundred extra weekly infections per one hundred thousand inhabitants in the fall of 2020 lowered leisure consumption by 36 percent and spending on durable consumption by 24 percent. We also show that this reaction in consumer spending is driven by the response of the elderly. For durable consumption, we find in addition that the overall decline is driven by a decrease in the likelihood of large purchases (relative to income). The effect on total consumption is much smaller and statistically not significant, pointing towards some substitution to other categories.

After Germany had experienced its first wave of the COVID-19 pandemic in the spring of 2020, infection rates, after a relatively calm summer, started to increase again in October 2020. The recommencement happened nationwide but unevenly across regions, see Figure 1. This second wave of the COVID-19 pandemic triggered the German government to institute a second lockdown on 2 November 2020, including the closure of restaurants, bars, clubs, and other leisure establishments.[1]

[1] Throughout this paper we use the term "lockdown" somewhat loosely, meaning any non-market based governmental restriction on leisure consumption activities, not necessarily a prohibition of free movement.

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*.

We exploit the spatially asynchronous unfolding of the second COVID-19 wave 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 heightened and varied infection risk but without substantial government restrictions in place. By contrast, any consumption development in the month of November is affected by lockdown measures. However, we can predict a counterfactual scenario to gauge how large the voluntary consumption drop would have been in November in the absence of the lockdown. Given the larger number of infections, on average 150 per hundred thousand inhabitants per week, the predicted leisure consumption drop (relative to no infections) for November would have been approximately 50 percent. This compares well to the actual decline between September and November, which means that the lockdown had little to no additional impact on leisure consumption. For durable consumption expenditures, we will show that the actual consumption development was better than the predicted counterfactual. Both results together suggest that lockdowns do not necessarily lead to excess economic losses.

In terms of data, we build on the *Sonderbefragung zum Konsum privater Haushalte 2020*, henceforth consumption survey, or, simply, survey. This ad-hoc survey was developed on behalf of the German Federal Ministry of Finance and with our conceptual input by the Federal Statistical Office (FSO). The FSO had a monthly survey on the consumption behavior of German households conducted from August until December 2020. In addition to socio-demographic and socio-economic data, the survey collected household aggregate and disaggregate consumption data retrospectively for the preceding month. Combining these data with the official disaggregate infection numbers and regional controls, we estimate a consumption equation with the coefficient on the number of local COVID-19 infections being 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, which is only superseded in case of a known different date of infection.

The literature on the economic effects of the pandemic is large (see, for example, Glover, Heathcote, Krueger, and Ríos-Rull, 2020; Bodenstein, Corsetti, and Guerrieri, 2022; Krueger, Uhlig, and Xie, 2022; Fuchs-Schündeln, Krueger, Ludwig, and Popova, 2022; Fuchs-Schündeln, Krueger, Kurmann, Lale, Ludwig, and Popova, 2023), but tight empirical estimates of behavioral responses to infection risk are still rare.[2] Yet, this response is key for 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 such that households reduce total consumption by less than 14 percent at the model predicted peak of the pandemic with roughly 5,000 infections per week and per one hundred thousand inhabitants (their Figures 1 and 2). Eichenbaum, Rebelo, and Trabandt (2022b,a) use consumption-infection elasticities similar to their earlier paper. Our point estimate for total consumption is, though insignificant, much higher: 5 percent per 100 weekly infections per one hundred thousand inhabitants. Kaplan et al. (2020) highlight that the response of consumption expenditures for those activities that exposes a household more strongly to infections, such as leisure consumption, can be expected to respond more strongly. Their macro-epidemiological model features a slower evolution of the epidemic than Eichenbaum et al. (2021), implying that under laissez-faire infections peak at around 1,500 infections per week and per one 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 peak, that is, at weekly infection rates of 6,000 per one hundred thousand inhabitants. Our estimated consumption response is stronger and predicts durable and leisure consumption to fall 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 consumption decline voluntarily chosen in a laissez-faire regime.

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

2 Data description

The consumption survey was conducted online from August to December 2020 in five waves (without a panel structure) at intervals of one month each. The FSO outsourced this task to the *Gesellschaft für Konsumforschung* (GfK), an independent institute specializing in such consumption surveys.[3]

At the heart of the survey are detailed questions on the realized consumption of the surveyed household

[2] Similar to our empirical strategy, von Gaudecker, Holler, Janys, Siflinger, and Zimpelmann (2020) estimates the labor supply response to infection risk in the Netherlands.

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

in the month preceding the survey. These questions were supplemented with 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 potentially willing to provide information, with approximately 40,000 active entries. From this, a stratified sample was drawn based on age, gender, household size, and Nielsen areas.[4] 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 for the sample of subsequent waves. The raw data were first adjusted by GfK using standard procedures[5] and made available to the FSO for the construction of further variables. Moreover, the sample weights of the consumption survey were adjusted such that it matches the population of the *2019 Mikrozensus* with respect to the multivariate distribution of household size, household type,[6] nominal net household income (categorical) and number of children under 18 living in the household. The place of residence of the household is recorded as their three-digit postal code. We focus on the survey months October and November, which, respectively, recorded September and October expenditures in order to avoid the direct lockdown effects (on November expenditures) and holiday effects in the summer months. This leaves us with approximately 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 on 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). 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 this to the three-digit postal code level.[7] Lastly, we add county-level information on population density and information on the number of hotel beds, a measure of tourism intensity.

[4]These individual characteristics were not interacted with each other. Nielsen areas are regional subdivisions of the federal states, which are primarily based on statistical considerations.

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

[6]Household types are: singles, couples without a child, couples with children, single parents.

[7] 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.

3 Results

3.1 Empirical patterns at the aggregate level

We start with a visual inspection of the changes in Engel-curves over the months September to November 2020, see Figure 2. The figure displays the 25th, 50th, and 75th percentile as well as average consumption by household net income groups and month for total consumption, social consumption and durable consumption expenditures. We define social consumption as expenditures on eating out, vacations, and ticket fees for entertainment and other leisure activities outside of people's homes. We split households based on whether they live in a three-digit postal code with above- or below-median infection risk in that specific month. As we mentioned before, infections are typically dated at the time of their registration through a positive test and is only superseded in case of a known different date of infection.

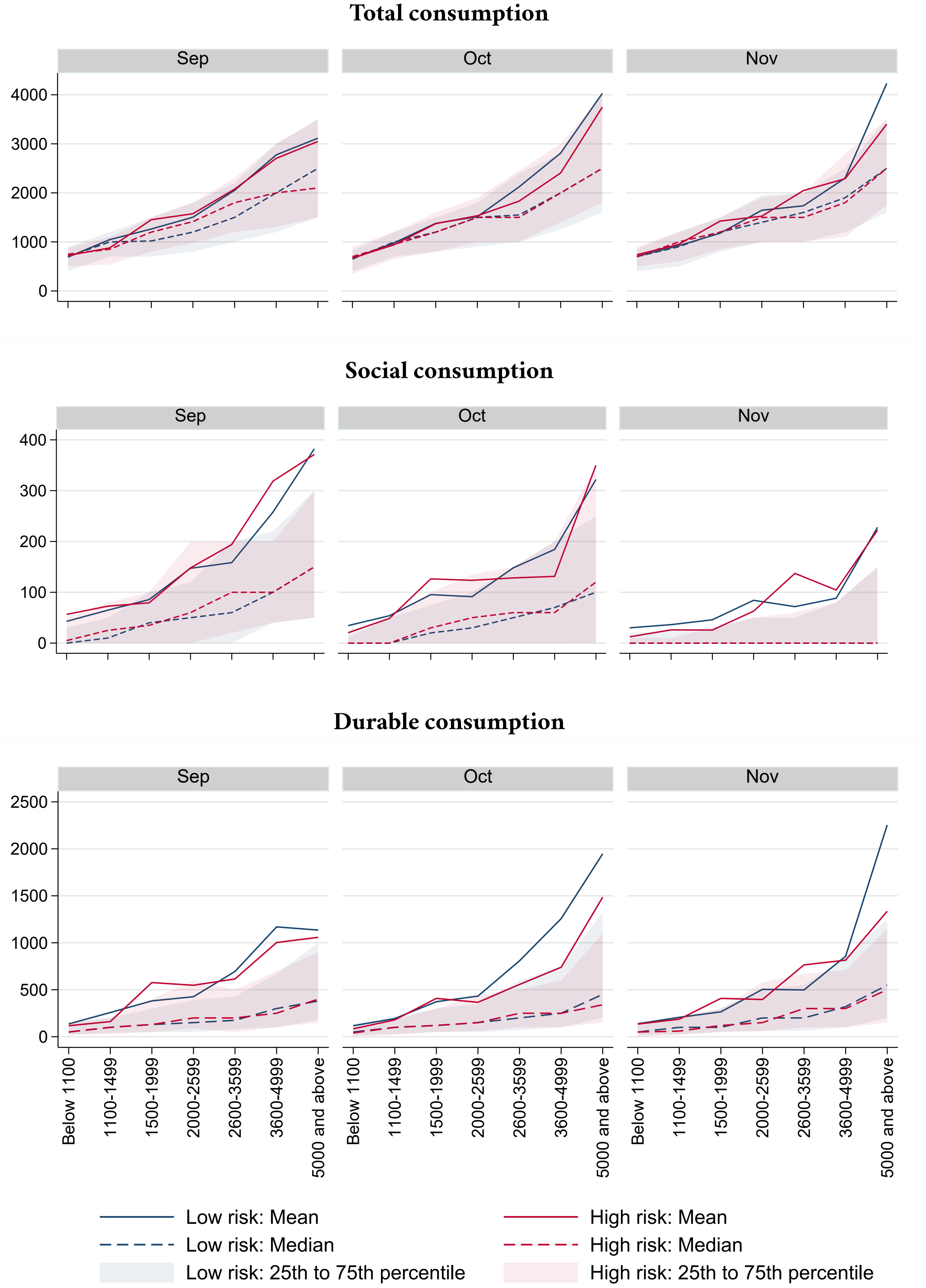
Perhaps surprisingly, the Engel curves for total consumption are approximately constant both across time and infection risk. If anything, there is some increase in total consumption in October and November. This likely reflects aggregate stimulus measures (see e.g. Bachmann et al., 2021, 2022, for a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

For social consumption, we see a steady decline of spending over the three months from September to November 2020. Casually, one might interpret this decline as indicative of an effect through heightened infection risk in October and the lockdown in November. However, the split of the Engel curves by local infection risk, which show an almost parallel decline of consumption spending in both groups, does not allow such a conclusion. The parallel consumption decline could be driven by seasonality, e.g., more inclement weather making social consumption less attractive. It could also be driven by aggregate infection risk developments. Finally, it might also be driven by endogeneity masking the response to infection risk when high social consumption regions experience higher infection rates, which are themselves caused by high social consumption.

For durable consumption, we see an increase in expenditures over time, in line with the findings on total consumption. Differently from total consumption, however, a wedge opens up between expenditures in high-risk and low-risk regions in October (and November): Average consumption is higher in low-risk regions. The comparison between median and mean consumption shows that differences are driven by a differential decline of particularly large expenditures. At a first glance, it might be surprising to find a negative effect of infection risk on durable good expenditures, given that the relative utility of durables should, if anything, go up in a pandemic with more consumption at home. However, durables need to be bought first, which, at least for larger and more expensive items, often requires a visual or otherwise physical inspection of the good, or perhaps advice from sales specialists. Plainly, to acquire certain durable goods one needs to go shopping, and in times of the pandemic this might be onerous.

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

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



Notes: Statistics of the cross-sectional distribution of expenditures for selected consumption categories by month and household net income group and by infection risk, measured by above- or below-median three-digit postal code level total infections in a month per one hundred inhabitants. Survey weights applied.

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:

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

The (inverse hyperbolic sign transformed, $IHS(c) = \log(c + \sqrt{c^2+1})$) consumption expenditures c_{it}^{u} of household i at time $t \in \{\mathtt{Sept}, \mathtt{Oct}\}$ (or, in a robustness check, $t \in \{\mathtt{Sept}, \mathtt{Oct}, \mathtt{Nov}\}$) 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 region 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).[8]

By controlling for regional fixed effects and further county-level characteristics, we take care of the fact that areas in which households consume more tend to be more prone to infections, our key threat to identification. This fixed effects treatment is sufficient because infections in the month of survey consumption are due to the incubation period largely determined by behaviour in the preceding month. Our measure of risk, therefore, exploits the time-series variation at the county-level.

In a robustness check, we replace the combination of two-digit fixed effects and county-level controls by a setup with only three-digit regional fixed effects (see Footnote 7 for details about the relationship between 3-digit postal code regions and counties). In a further robustness check, we measure infection risk using infections from only the first two weeks of a given month. Thereby, we ensure that infections stemming from within-month consumption decisions are not included on the right-hand side of the regression. All robustness checks can be found in Appendix III.

3.2.1 Main results

In the left panel of Table 1, we present our baseline results, that is, estimating equation (1) with $t \in \{\mathtt{Sept}, \mathtt{Oct}\}$. We find a negative but insignificant effect of infection risk on total consumption expenditures. 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, however, large: 5 percent per 100 weekly infections per one hundred thousand inhabitants. What is more, the insignificant aggregate effect masks heterogeneity across different consumption categories. Not all consumption exposes the consumer equally to infection risks. Social consumption comes with the highest exposure and thus, in line with what has been hypothesized in the literature (Kaplan et al., 2020), responds the most to infection risk. Also—perhaps surprisingly at first glance—expenditures on durables respond significantly. This likely

[8] Similarly to infection rates, these three variables are measured at the county level. We match these variables to each household based on their 3-digit postal code region which we observe in the data using the same aforementioned procedure. All county-level measures are time-invariant. The time subscript in $\boldsymbol{X}_{it}$ merely indicates that our household sample consists of repeated cross-sections.

reflects that the purchase of durables is often characterized by two features: First, as described above, a shopping trip is essential for a visual inspection, and second, this shopping trip can be postponed. By contrast, expenditures on groceries do not react to infection risk. Whereas they, too, may require a shopping trip, groceries are harder to postpone even if infections rise.

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
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. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. The estimated coefficients for all controls can be found in Table A.4.

The effects on social and durable consumption expenditures are also economically significant. An extra one hundred infections per one hundred thousand inhabitants and week lead 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 durables. We can put these effect sizes into perspective, both through the time series dimension of infections as well as through a cross-sectional perspective. Infections went up by circa fifty cases per one hundred thousand inhabitants and week between September and October (see Figure 1), implying that the expected consumption drop is roughly halve of the numbers above. Fifty cases per one hundred thousand is also roughly the difference between the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentile of the infection risk distribution across counties in October, see, again, Figure 1.

Relatedly, we can also use our estimates to compute counterfactual scenarios about how consumption would have dropped in the absence of lockdown measures given the households' response in October 2020. In Germany, infections reached numbers as high as 750 or 1200 per one hundred thousand inhabitants and week at the peak of the pandemic in 2022 after the vaccination campaign allowed largely a return to pre-pandemic rules and behavior. Our estimates imply that at these infection numbers consumption would have collapsed almost completely (more than -95 percent for social consumption) had the vaccines not changed the health risks. This underscores the enormous economic value of the vaccines.

Similarly, given the (comparably smaller but still large) number of infections in November 2020, on average 150 per one hundred thousand inhabitants, the predicted leisure consumption drop (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 to the actual decline between September and November, which means that the lockdown measures had likely little to no additional impact on leisure consumption.

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

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

3.2.2 Robustness checks

Potentially, our baseline estimates might suffer from a (downward) bias because some households spend nothing on a given consumption category in a given month. Not only for durables, but also for social consumption this is potentially an issue, since about nine percent of households in our sample report zero expenditure for durable goods and even a third indicates that they did not spend anything on social consumption. Reassuringly, our results are robust when estimating a Tobit model, that accounts for censoring at zero, see Appendix III Table A.5. Consistent with the notion that censoring induces a bias towards 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 home county. Therefore, we can expect households to also react to infection risk beyond their county of residence. In particular, this is likely to hold true for purchases of larger durables. We, therefore, repeat our estimation with an alternative measure of infection risk calculated as the infection risk in a 30km radius around the home county,[9] and present the results in Appendix III Table A.6. We find qualitatively similar negative effects of infection risk on consumption expenditures. For social and durable consumption, the effects are quantitatively even stronger. In particular, this holds true for durables, as expected.

The hypothesis that infection risk could change households' consumption expenditures builds on the fact that most consumption entails social contact. Yet, that very fact could generate a force of reverse causality: *Exogenous* shifts in consumptioncould increase infections, introducing a positive correlation between consumption infections and thus possibly biasing our estimates downward.[10] To gauge the magnitude of such a potential bias, we exploit the incubation period of the virus of one to two weeks: Exogenous consumption shocks will generate additional COVID-19 infections that will mostly occur and be registered during the third or fourth week of the month (and the first weeks of the next month), unless those shocks are bunched at the beginning of a given month. Hence, infections registered and reported during the first two weeks of a month should be much less affected by such shocks and hence be largely exogenous to households' consumption choices within the month. Appendix III Table A.7 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 so as to facilitate comparison of coefficients across specifications). In fact, point estimates do increase notably, indicating that reverse causality possibly makes our baseline estimate somewhat conservative. However, estimation precision declines, presumably because our measure no longer captures all relevant infections.

As a final robustness check, we use more finely grained regional fixed effects. These region fixed effects are key to our identification as they filter persistent consumption and infection differences across regions that could confound estimates of risk sensitivity. Constrained by sample size, our baseline estimation controls for 2-digit postal 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 which uses the full set of county-level fixed effects in Appendix III Table A.8. The results are virtually unchanged.

3.2.3 Durable consumption expenditures

As we have shown in the previous sections, there is a statistically and economically significant negative effect of infection risk on spending on durable goods. Durable goods expenditures in the survey are the

[9] For any given county, we add to its monthly infections the infections from other counties whose centroids fall into the 30km radius around its centroid. We repeat the procedure for population and divide total infections by total population. We compute this spatially broader infection risk measure for every county and month and match the data to household survey information at the 3-digit postal code level following the procedure previously described in Footnote 7.

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

sum of spending on vehicles, home appliances and furniture, apparel, and an other category. Therefore, we re-estimate equation (1) with consumption expenditures for subcategories of durable goods. Moreover, in order to obtain a decomposition of the total effect, we use expenditures relative to household net income as the left-hand side variable.

Table 2: Effect of infection risk on durable expenditures, IHS and as a share of income

	IHS-transformed expenditures				expenditures as share of income			
	durables	home	apparel	vehicles	durables	home	apparel	vehicles
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(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
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: Regressions of consumption expenditures as a share of net household income for each durable consumption category for the September-October sample (right panel). 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 2 shows the results. The first column replicates the baseline results for durable consumption expenditures presented before. Columns two to four report expenditures sensitivities for subcategories being very similar to the aggregate sensitivity, except for virtually no response for vehicle purchases. Columns five to eight shows results for consumption expenditures as shares of household income.

Also in this specification, infection risk affects durable expenditures negatively. One hundred more regional infections per one hundred thousand inhabitants and week reduce the expenditure share on durables by 7.7 percentage points. The largest contribution comes from vehicle purchase, though statistically not significant because such purchases are rare, see Table A.3 in Appendix II. The next two categories are home appliances/furniture and apparel, where infection risk indeed has an economically and statistically significant negative effect; together a little more than a third of the overall effect.

In Table 3, we employ quantile regressions to investigate where in the distribution the effects stem from. We focus on consumption expenditure shares to filter income effects from the distribution of which we estimate the quantiles. One would expect that households cut especially large durable purchases that require a more thorough inspection and/or advice from sales professionals, and thus a social interaction with potential for infection exposure. The results in Table 3 confirm this conjecture both for expenditures on durable goods overall as well as for the home appliances/furniture and apparel subcategories.[11]

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

Table 3: Quantile effects of infection risk in the county of residence on durable expenditure shares

	OLS	Q50	Q75	Q90	Q95
	(1)	(2)	(3)	(4)	(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 net household income for durable consumption categories. Estimates at the 50^{th}, 75^{th}, 90^{th}, and 95^{th} percentile for the September-October sample. Otherwise identical to baseline specification, see notes of Table 1. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

3.2.4 The effect of age

A key feature of the COVID-19 disease was a steep gradient of severity and mortality in age. For persons below the age of 40 infections had in most cases relatively mild consequences (Gallo Marin et al., 2021). This fact was well-known by autumn 2020. Ergo, one would expect a much stronger sensitivity of consumption behavior to infection risk by older cohorts. To test this hypothesis, we split the sample along the median age of household heads, which in our dataset is 40, and estimate two separate sensitivity parameters for each consumption category.

Table 4 shows the results both for social and durable consumption expenditures. Columns one and four reproduce the baseline results. Columns two and five split infection sensitivity by age.

Indeed we find that only the reaction of older cohorts to infection risk is statistically significant and about twice as large as that for younger cohorts. The difference in the sensitivities is particularly strong for social consumption. Nonetheless, we also find a sizable negative, albeit insignificant, infection risk sensitivity for the young.

Expenditures for both durables and social consumption increase with income and wealth, which, in turn, tend to increase with age. Hence, infection risk sensitivities may be smaller for the young for the mechanical reason that they spend little on either consumption category. To test this, we add an additional interaction with household wealth, split at 50,000 Euro, roughly the median in our data. Columns three and six of Table 4 display the estimated risk sensitivities for each subsample. Reassuringly, effects are still concentrated among the older cohorts. Notably, we detect an interesting heterogeneity within the old: It is the old and wealth-poor who respond the most in their durable consumption expenditures, whereas it is the old and wealth-rich who respond particularly strong in social consumption expenditures. This pattern mirrors the relative level of the good's consumption expenditure share in September of 2020; see Table A.3 in Appendix II. The old and wealth-poor spent particularly little on social consumption, likely a luxury for them (4 percent of their income compared to 7 percent for the wealth-rich), and the old and wealth-rich spend little on durables (18 percent of their income compared to 20 percent for the wealth-poor), they likely own most durables they need already. It is for these different categories of consumption, social and durables, where the respective household types have less maneuverability to reduce spending in the first place.

Table 4: 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 $\times$ poor			-0.165			-0.164
			(0.217)			(0.249)
Infection risk, young $\times$ rich			-0.302			-0.046
			(0.248)			(0.307)
Infection risk, old $\times$ poor			-0.444**			-0.160
			(0.191)			(0.218)
Infection risk, old $\times$ 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
N	7008	7008	6053	7008	7008	6053
R^2	0.11	0.13	0.14	0.15	0.17	0.19

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

4 Conclusion

In this paper, we ask what effect local COVID-19 infection risk had on consumption expenditures before vaccinations were available. We use a high-quality survey of household consumption designed by the German federal statistical office to monitor the consumption dynamics during the pandemic and the response to policy interventions.

We use within-county variations in infection risks to identify the consumption response to infection risk and find that they lead to a decline in consumption spending. While the effect is sizable, it is statistically insignificant for total consumption. For social consumption and expenditures on durables, the effect is both economically and statistically significant and much larger than what many macroeconomic models of the pandemic are calibrated to. Households apparently did cut consumption to avoid being exposed to the virus, to avoid infection. This interpretation is supported by the fact that the reduction of consumption was particularly strong amongst the elderly.

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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

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, 75^{th} percentile	0.83	0.05	0.19	0.17	0.08	0.06	0.00
Expenditures as share of income, 90^{th} percentile	1.08	0.13	0.25	0.38	0.25	0.09	0.00
Expenditures as share of income, 95^{th} 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 4 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.

III Robustness

Table A.4: 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.5: 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
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.4. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.6: 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
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.7: 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
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.4. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.8: 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
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.4. 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?