Appendix to
"Expected Post-Pandemic Consumption and Scarred Expectations from COVID-19." 2021.
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We quantify the patterns from the figures via regression exercises. We regress each individual *j*'s expected post-pandemic usage of a service on a large set of explanatory variables from our survey, following the breakdowns set out in Figures 4 through 6, along with other controls.[1] Table A1 contains the list of variables and the coefficient estimates for each post-pandemic usage question. In the table, the indicator function I(.) takes the value of 1 for individual *j* if the expression inside the parentheses is true and 0 otherwise. Without belaboring each entry in the table, we make the following observations.

- We capture the U-shaped pattern—of early pessimism about post-pandemic usage followed by subsequent optimism—by including measures of time and time-squared in the regression, where time is measured in days after April 3, 2020, which is the first day in our sample.[2] After including a variety of controls, our coefficients are negative on time (line 1), positive on time-squared (line 2), and highly statistically significant. Without this nonlinear time trend, it is difficult to explain the down-up pattern in beliefs with other controls, which were either included in the regression or tried and dropped because they were not statistically significant.
- For respondents older than 60 years old (line 4), we see the largest negative coefficients, ranging from −9 to −16, consistent with markedly lower expected usage than the control group, which in this case is individuals less than 40 years old.
- Other groups for which we find negative coefficients, indicating expected lower usage, include middle-aged respondents (defined to be between 40 and 60 years old, line 3); respondents who expect that the coronavirus outbreak will last for a relatively long time (lines 7 and 8); and respondents who live outside of a metropolitan core (line 9).[3]
- High-income respondents with household incomes above $100,000 per year (line 11) have the largest positive coefficients, ranging from +9 to +11, consistent with markedly higher expected usage than the control group, which in this case is individuals with household incomes below $35,000 per year.
- Other groups for which we find positive coefficients, indicating expected higher usage post-pandemic compared with pre-pandemic, include individuals with post-graduate degrees (line 6); respondents from middle-income households (line 10); respondents who identify as Black

[1] We report the results from a linear regression for ease of interpretation; the reported coefficients are extremely similar to what we would have reported if we transformed our 0 to 100 slider values to a [0,1] range, estimated the regression using a fractional logit model, and then calculated the marginal effects from the 0 to 100 range of our original slider.
[2] Including only time in the regression would capture a linear time trend. In order to capture the down-up pattern, we need a quadratic term in the regression, time-squared. As another way to capture the trends over time, we also ran regression specifications featuring monthly fixed effects. The time fixed effects then captured the down-up pattern we document; the other coefficients in our regression were little changed from this alternative specification.
[3] We compare each individual's zip code with metropolitan area code definitions from the United States Department of Agriculture. For more information on the USDA codes, see: https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes/documentation/.

or African-American (line 12); respondents who identify as Hispanic (line 13); respondents who have children (line 14); and respondents who identify as male (line 15).[4]

Table A1: Regression results.

	Hospitality usage	Public transportation	Crowded events
1. Time	-0.04***	-0.04***	-0.05***
	(0.01)	(0.01)	(0.01)
2. Time-squared	2.0e-4***	2.0e-4***	2.4e-4***
	(1.6e-5)	(1.7e-5)	(1.6e-5)
3. I(age between 40 and 60)	-4.8***	-6.8***	-7.2***
	(0.3)	(0.3)	(0.3)
4. I(age>60)	-9.0***	-13.5***	-16.3***
	(0.3)	(0.4)	(0.3)
5. I(education=bachelor's degree)	0.4	1.8***	-0.1
	(0.3)	(0.3)	(0.3)
6. I(education=post-graduate degree)	4.6***	7.5***	4.6***
	(0.4)	(0.4)	(0.4)
7. I(outbreak duration=2-3 years)	-4.4***	-3.8***	-5.0***
	(0.3)	(0.3)	(0.3)
8. I(outbreak duration>3 years)	-7.4***	-6.0***	-7.6***
	(0.4)	(0.5)	(0.5)
9. I(live outside of a metropolitan core)	-1.2***	-4.0***	-1.1***
	(0.3)	(0.3)	(0.3)
10. I(income between $35k-$100k)	4.4***	2.7***	3.0***
	(0.3)	(0.3)	(0.3)
11. I(income>$100k)	10.7***	10.2***	8.9***
	(0.4)	(0.4)	(0.4)
12. I(identify as Black or African-American)	0.7	2.6***	1.0**
	(0.4)	(0.5)	(0.4)
13. I(identify as Hispanic)	2.5***	3.3***	3.0***
	(0.5)	(0.5)	(0.5)
14. I(report having children)	3.9***	3.1***	4.4***
	(0.3)	(0.3)	(0.3)
15. I(identify as male)	5.2***	6.1***	5.8***
	(0.3)	(0.3)	(0.3)
16. Constant	44.9***	41.0***	44.6***
	(0.5)	(0.5)	(0.5)
Observations	38,362	38,362	38,362
R-squared	0.11	0.14	0.14

Notes: Standard errors in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.
Source: Federal Reserve Bank of Cleveland.

[4] CDC data find large disparities across race and ethnicity in COVID-19-related mortality rates in the United States. After standardizing for age, the distribution of COVID-19 deaths is skewed toward Hispanic and Non-Hispanic Black groups. See https://www.cdc.gov/nchs/nvss/vsrr/covid19/health_disparities.htm. In our regression results, however, we do not find the same broad expectations scarring across these groups as we do among Americans older than 60. While it is possible that the differential skewness across racial and ethnic groups is much smaller than that across age groups, which helps to explain these differing results, further research into the topic is necessary. The finding that men report higher expected post-pandemic usage than women could be related to differing risk tolerances across gender groups; see Borghans et al. (2009).

Reference

Borghans, Lex, James J. Heckman, Bart H. H. Golsteyn, and Huub Meijers. 2009. "Gender Differences in Risk Aversion and Ambiguity Aversion." *Journal of the European Economic Association*, 7(2-3): 649–658. https://doi.org/10.1162/JEEA.2009.7.2-3.649.