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Risk Creep: A COVID-19 Longitudinal Field Study

Jennifer M. Logg

Catherine H. Tinsley

Matthew R. Leitao

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Jennifer M. Logg
McDonough School of Business
Georgetown University

Catherine H. Tinsley
McDonough School of Business
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Matthew R. Leitao
Psychology Department
Georgetown University

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Jennifer M. Logg
McDonough School of Business
Georgetown University

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Psychology Department
Georgetown University

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Correspondence concerning this article draft should be addressed to Jennifer M. Logg, McDonough School of Business, Georgetown University, Washington, DC 20057. E-mail: jenn.logg@georgetown.edu.

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Abstract

How do norms evolve to influence behavior over time? The global COVID-19 pandemic introduced immense uncertainty; six months into the pandemic witnessed no foreseeable ending and no available vaccine. Given that people could not quarantine indefinitely, they needed to develop new social norms, rules of appropriate behavior. Across eight weeks, we tracked the behavior of university students as they returned from lockdown to campus at an east coast university. Students' behavior is associated with both 1) social learning (what they saw others doing) and 2) experiential learning (reflecting on the perceived risk associated with their own past behavior). Social learning affects three types of discretionary activities outside of the home: exercising, socializing in smaller groups, and attending larger events. Controlling for a number of factors, regression results show that the more students see or hear about others doing one of these activities, the more likely they are to engage in that activity the following week. We call this gradual increase in precarious activity, "risk creep." A creeping tolerance for risk for two of these activities also occurs within an experiential learning paradigm. Specifically, the riskier students judge their prior week's behavior (which, on average, had little negative consequence), the more likely they are to leave their home the following week for exercise and large events. Together our results suggest that norms for discretionary activities evolve over time based on both social learning cues and experiential reflection of risk and consequences.

Keywords: Norms, Risk Perception, Decision-Making, COVID-19

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Significance

How do norms evolve? During the pandemic, post-lockdown and pre-vaccine, it was not clear which behaviors were appropriate. Across eight weeks, we tracked people's behaviors and perceptions to understand how risk perceptions, sensemaking, and decisions evolved over time. First, we establish a record of behavior outside of the home during this time. Second, we analyze correlates between these behaviors, observed norms, and perceptions of risk over time. Behavior is associated with both 1) social learning (what they saw others doing) and 2) experiential learning (reflecting on the perceived risk associated with their own past behavior). Both social and experiential learning are associated with a gradual increase in precarious activity, what we call "risk creep."

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Risk Creep: A COVID-19 Longitudinal Field Study

How do behavioral norms evolve to influence behavior? The onset of the global COVID-19 pandemic created a natural disruption to social routines, allowing us to examine how norms form and develop over time. The world entered a global lockdown of home isolation. As people subsequently emerged from lockdown in 2020, prior to vaccination, they faced more uncertainty around expectations of behavior than they had in their lifetime. This context required creating new norms regarding appropriate behavior. In a 5-month longitudinal field study, we tracked what people did when they left their homes and how those choices were associated with social cues based on observing others' behavior as well as their own experiential trial-and-evaluation processes. Thus, this field study focuses on two behavioral correlates, 1) *social learning* based on cues from others and 2) *experiential learning* based on how people perceive the riskiness of their own past behavior.

With the onset of the pandemic, people around the world simultaneously questioned which behaviors were appropriate in order to reduce both individual and societal risk of exposure to COVID-19. The uncertainty in this new world (dis)order shattered customary living routines. People likely relied on social cues to inform their behavior, what we refer to as *social learning*. Decades of research shows that people's behavior is highly influenced by observing what others do, especially in uncertain situations (Cialdini 2001). Canonical work on Social Learning Theory highlights that social context (observing how others conduct themselves and subsequent consequences) is sufficient for learning new behaviors (Bandura & Walters, 1977). Descriptive norms guide behavior as people make inferences about what is customary (Cialdini et al., 1990; Goldstein et al., 2008; Roberts et al., 2017; Roberts et al., 2019; Roberts et al., 2021; Shealy et

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al., 2018). Additionally, injunctive norms influence behavior because people make inferences about what behavior is socially endorsed or censured (Schultz, et al., 2007).

COVID-19's major disruption to "normal" routines likely led people to first ask, *what are other people doing?* (i.e., descriptive norms). This does not imply that people fail to make inferences about injunctive norms. In fact, sometimes norms themselves are not enough to shift behavior (Rinscheid et al., 2021). But in the summer of 2020, as people first emerged from lockdown, there was little social agreement regarding which activities should be sanctioned or censured. Thus, descriptive norms are more likely to become the basis for social learning within this highly uncertain context.

Given the lack of formal guidance during this phase and the awareness that no one else's behavior was a perfect model, *experiential learning* may also guide behavior. This experiential learning likely involves a trial-and-evaluation sense-making such that people test behaviors, make a post-hoc assessment of the risk associated with these activities, and adapt to maintain a tolerable risk level. Extant research shows that rather than assessing risk cognitively, people often use their emotions to perceive and interpret risk associated with their behaviors, called "risk as feeling" (Lowenstein, Weber, Hsee, Welch, 2001). Thus, people may compensate for feelings of overly risky behavior one week by engaging in fewer risky behaviors the following week. For example, in Peltzman's risk compensation model, people adjust their behavior to perceived risk, acting more carefully when they sense greater risk in the environment (Peltzman, 1975). Alternatively, if people sense greater safety (because they engaged in risky behaviors with no serious consequences), they may become less careful with their behavior (Peltzman,

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1975).[1] We suggest this could lead to a creeping risk tolerance reflected in increasing engagement in behaviors that puts individuals at greater risk for exposure to COVID-19, what might be considered a "risk creep."

This latter process is instantiated in work on near-misses, events that could have resulted in a negative outcome but, by chance, did not. Work with lay people and experts alike shows that individuals tend to process near-miss events as successes. By discounting the probability of a bad outcome, they subsequently engage in either riskier behaviors or a greater number of risky behaviors (c.f. Dillon & Tinsley, 2008; Reason, 1990; Tinsley, Dillon & Madsen, 2011). Near misses can lead people to underestimate the likelihood of danger in similar situations, leading to riskier decisions (Tinsley et al., 2012). Emerging from lockdown, people may make similar inferences. They may reflect on how comfortable they feel leaving home for certain activities and whether they experience negative consequences (contracting COVID-19). Absent immediate negative consequences, they may engage in more activities such that risky activities increase surreptitiously over time.

We examine the evolution of behavioral norms by measuring the impact of social learning (from observing others' behavior), and experiential learning (from people reflecting on the risk associated with their own behavior). To our knowledge, previous work has not connected the literature on social learning and risk perceptions to examine how new norms evolve. Our work also establishes a record of behavior outside of the home during the new, post-lockdown and pre-vaccine, pandemic environment. Over five pivotal months (August 17-December 15, 2020), we track the behavior of three waves of students who return from

[1] Indeed, what Peltzman found, somewhat ironically, is that seatbelt laws contributed to more traffic accidents (though fewer fatalities for drivers) because drivers felt more protected by the seatbelt.

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lockdown to an east coast university and its surrounding neighborhood in order to take classes remotely. To understand broader trends for how people experience life after lockdown, we measure the frequency of specific activities people did when leaving home.

Tracking the frequency of activities over time allows us to measure changes in decisions related to leaving home and thus potential exposure to contracting COVID-19. We believe our research is the first to analyze correlates between behavior outside of the home, risk perceptions, sensemaking, and decisions over time during the COVID-19 global pandemic following the first US lockdown.[2] Some work has examined associations between morality, prosocial attitudes, and individual differences with avoiding physical contact, hygiene, and support for COVID-19 policies throughout different points in the pandemic (Pavlović et al., 2022).

Our results show that the frequency of certain discretionary activities creeps higher the more an individual observes others taking part in that same activity. We call this increase in activity frequency "Risk Creep" because more activities suggest a "creeping" of risk tolerance for activities that could potentially lead to greater exposure to contracting COVID-19. Similarly, we find that the frequency of some discretionary activities creeps higher the riskier an individual judges their own behavior the prior week. This creeping increase in activities mirrors the near miss results that people become complacent about a hazard's risks over time. If they perceived the activities as riskier but fail to contract COVID-19, this may increase people's willingness to incur risk with a greater number of activities.

Although panic about COVID-19 has subsided, the likelihood of another disruptive event creating sustained periods of behavioral uncertainty remains: new variants can spread at higher

[2] Some work tracks preventative behaviors, such as mask wearing (Kwon, Sohee, et al. 2021, Byrne, K. et al., 2020) and some tracks day-to-day behavior in the home during lockdown (Sullivan et al., 2021).

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rates and new viruses could emerge. We may again face environments of high uncertainty about appropriate behaviors. It is therefore useful to chart how people use observations of others' behavior and perceptions of risk associated with their own behavior to inform actions that can collectively generate new norms.

Results

We collected data using a baseline survey (Survey 1) and 7 weekly follow-up "pulse" surveys, which include a subset of questions from Survey 1. The 7 pulse surveys are key to our data analysis as they allowed us to track changes in behavior and perceptions over time. In all surveys, participants reported the number of times they left their home to engage in 6 different categories of activities. During data analysis, we organized them into two higher-order categories, 1) non-discretionary activities, necessary for day-to-day living (going outside the home for exercise, small social gatherings, and large events outside of the home) and 2) more discretionary activities, which were relatively less essential for day-to-day living, and were foregone by many during lockdown (going outside the home to dine, run errands, and for school activities).

To examine social learning, participants reported how many people they saw taking part in those same activities. We named this variable *number of others observed*. To examine experiential learning, we measured people's perceived risk of their own past behavior. We named this average numeric score *perceived risk*.

Post Lockdown Pandemic Behavior. Our data focus on behaviors that potentially expose students to the risk of contracting COVID-19 (e.g., contact with others outside their households). Figures 1A-F show the results of our regression analyses for social learning. As

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expected, the slopes are positive and significant for the relationship between the *number of others observed* in the past week and three discretionary activities in the current week: exercise, small gatherings, and events. Figures 2A-F show the results of our regression analyses for experiential learning. The slopes are positive for the relationship between *perceived risk* of the past week and level of those same activities in the current week (but not all significant at $p < .01$).

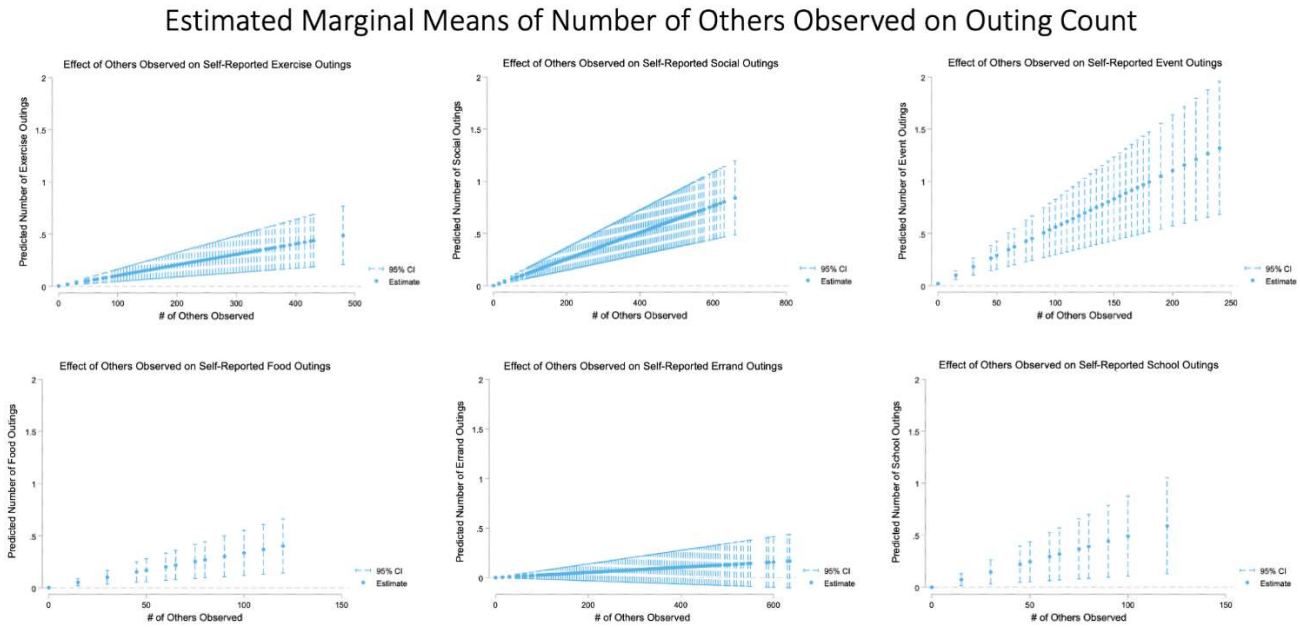


Figure 1A-1F. Number of others observed taking part in a specific activity last week and the number of self-reported outings for that activity this current week. From upper left clockwise, Discretionary: Exercise, Social, Event; Non-Discretionary: School, Errand, Food.

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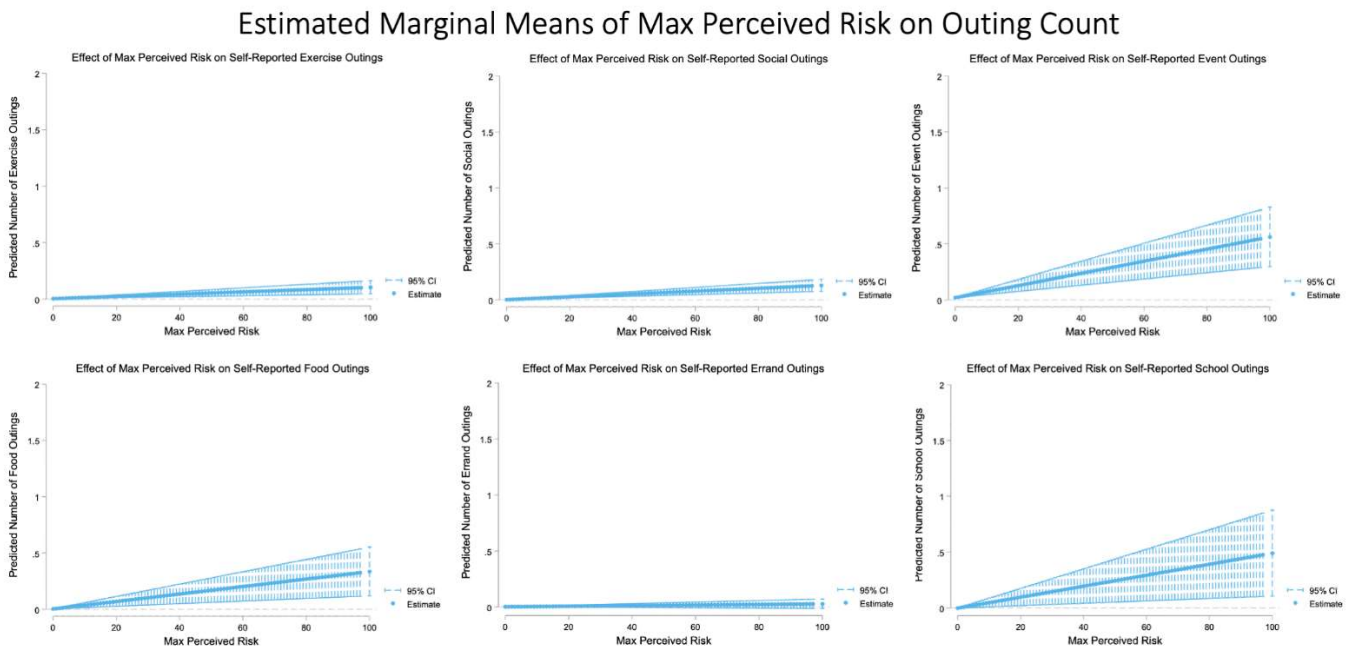


Figure 2A-2F. *Perceived risk* of last week's activities and the number of self-reported outings for that activity this current week. From upper left clockwise,
Discretionary: Exercise, Social, Event; Non-Discretionary: School, Errand, Food.

Demographics. As Table 1 shows, a few demographic effects are stable across all models [controls only (Models 1a-1f), with main effects (Models 2a-2f), and with main effects and interaction terms (Models 3a-3f)]. Students with more roommates are more likely to leave their house to get food and less likely to go out for school-related activities. Students who are more conservative report attending more large events. Seniors are more likely than underclass students to get together for a small social gathering and to run an errand. Students who participate in the third (final) wave of data collection (starting September 14, 2021) report more school-related activities than students who participated in earlier waves. Female students report engaging in more activities than male students, including small social gatherings and running errands, though these effects become non-significant when interaction terms are added.

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	Model 1			Model 2		
	Exercise Count	Social Count	Event Count	Exercise Count	Social Count	Event Count
Constant	.015	.024	-2.724***	-.319*	-.435**	-4.494***
	(.131)	(.135)	(.459)	(.140)	(.157)	(.498)
Number of Outings T-1	.304***	.223***	.419***	.287***	.201***	.274***
	(.013)	(.013)	(.067)	(.014)	(.013)	(.057)
Female	.045	.196***	.114	.021	.170**	.001
	(.049)	(.058)	(.188)	(.048)	(.058)	(.176)
# Roommates	.010	.012	.066	.004	.005	.070
	(.013)	(.015)	(.044)	(.012)	(.015)	(.043)
Politics: Liberal (1) to Conservative (7)	-.006	.005	.324***	-.014	-.002	.366***
	(.018)	(.022)	(.058)	(.018)	(.022)	(.058)
1[Class= Senior]	.027	.234***	.193	.041	.247***	.218
	(.055)	(.069)	(.194)	(.054)	(.068)	(.174)
week	-.030**	-.050***	-.055	-.025*	-.045***	-.035
	(.011)	(.010)	(.034)	(.011)	(.010)	(.036)
1[Wave=1]	.049	.114	-.496	.033	.112	-.566
	(.063)	(.088)	(.282)	(.064)	(.087)	(.306)
1[Wave=3]	-.009	.096	.095	.015	.100	.206
	(.055)	(.063)	(.205)	(.054)	(.062)	(.184)
Number of Others Observed T-1				.001**	.001***	.006***
				(.000)	(.000)	(.002)
Risk Perception Max. T-1				.005***	.002*	.020***
				(.001)	(.001)	(.003)
lnalpha	-1.065***	-.432***	1.859***	-1.141***	-.486***	1.570***
	(.175)	(.099)	(.149)	(.179)	(.102)	(.144)
Observations	1638	1638	1638	1637	1634	1634

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

Table 1. *Number of discretionary activities* reported in the current week (Exercise, Social, Event) as predicted by the *number of others observed* and *perceived risk* both in the prior week, controlling for the number of outings in the previous week and demographics.

Discretionary Activities: Exercise, Small Social Gatherings, & Large Events

Social Modeling. All three discretionary activities are significantly and positively correlated with *number of others observed* in the prior week as seen in the coefficients for *exercise, small gatherings,* and *large events* (Table 1 Model 2a-2c). The more students see others engaging in a particular activity during the prior week, the more likely they are to engage in that

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same activity during the current week. We call this increase in activities from week to week a "risk creep" as it reflects a creeping tolerance in risk.[3]

We should note that overall, the number of activities outside of the home decreases over time (see the negative coefficient for *week*) as does the number of students engaging in activities outside of the home. For the percentage of participants reporting an activity at least once the previous week, see Appendix Figure 1A-1F. But not all students uniformly decrease their discretionary behavior. For a subset of people who test the waters by engaging in discretionary activities outside of the home, they observe others doing the same. This observation serves as a social cue, reinforcing this behavior the following week. Thus, despite a decrease in activities over time for the *sample*, social modeling still accounts for variance in *individual* behavior. While social modeling is associated with variance in behavior at the individual level, increasing certain students' discretionary behavior, might perceived risk of one's own behavior be similarly associated with a creeping increase in activities?

Perceived Risk of Past Behavior. Two discretionary activities, *exercising* and *attending large events*, were associated with *perceived risk* of past behavior, as seen in the significant positive coefficient in Models 2a and 2c. For *small gatherings*, Model 2b shows a main effect only significant at the $p<.05$ level (below our cutoff). Together, these results suggest a risk creep connected to experiential learning. When students perceive their activities in the prior week were overall riskier, they leave the house more for exercise and to attend large events the subsequent week.

[3] Note that across all 6 dependent variables, the number of times students did an activity in the prior week was highly predictive of doing the same type of activity in the current week, and our regression results control for this.

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Again, while behaviors for the entire population decrease over time, for a subset of people who test the waters, they acknowledge that their behaviors incur more risk. Although these students self-reported taking more risk, they likely experienced no negative outcomes, as only 14 out of the 303 participants reported testing positive during the months of the study. With such a small COVID-19 rate, logistic regressions to test whether certain activities lead to greater chances of contracting COVID-19 were not stable (though bivariate correlation was significant between large events and contracting COVID-19. See Appendix Table 1).

Non-Discretionary Activities: Food, Errands, and School Projects

There is little impact on food, errands, or school-related activities from either *number of others observed* or *perceived risk*. Although there is a main effect for *number of others observed* on food and school-related activities, these effects become non-significant when demographic interaction terms are introduced to the model. Similarly, there is a main effect for *perceived risk* on food, but again this effect disappears when demographic interaction terms are introduced. See Appendix for robustness checks.

Discussion

Creating a global disruption to social behavior, the COVID-19 pandemic produced a unique context for documenting the evolution of incipient behavioral norms. This disturbance is arguably the first time in our lifetimes that people around the world simultaneously faced such grave uncertainty around appropriate public behavior. Both social learning (observing others) and experiential learning (people's perceived risk of their past behavior) are associated with increased discretionary activities outside the household. As one might expect, neither social nor experiential learning influence non-discretionary activities.

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Our results suggest a creeping tolerance of risk for activities that mirrors prior results showing people become complacent about risks over time (Dillon & Tinsley, 2008; Reason, 1990; Tinsley et al., 2011; 2012). In our data, the more people see others engaging in certain discretionary activities outside of the home (exercise, small gatherings, and large events), the more often they themselves engage in these same activities, suggesting a social learning model. We also see evidence of experiential, trial-and-evaluation, learning. Those predisposed to engage in riskier public activities during the pandemic gradually engage in more subsequent discretionary activities the following week.

Overall, social and experiential learning account for variance in activities outside the household, despite the overall decrease at the sample level in the percentage of students engaging in activities over time. If people learn from observing others' behavior and only observe others who leave the home, either while they themselves are out or via social media, then perceptions of the new normal may be biased because staying home is less visible. Thus, social learning may be biased by the same phenomena that produce pluralistic ignorance, wherein the minority behavior is perceived as more widespread than it is (Prentice & Miller, 1993). As people follow friends and aspirational people on social media, they likely self-select into receiving information from similar others, thus increasing the likelihood of selection bias for the type of information they observe. While our data can't speak directly to this causal relationship, social desirability is a possible driving mechanism as it seems most directly related to social media.

Whether the creeping increase in activities is due to Bayesian updating of the behavioral risk they reported (exercise and large events) or because people feel differently about the same level of risk associated with these activities remains unknown. Our data can only speak to the overall pattern of behavior that shows a creeping engagement in more discretionary activities

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(exercise, small gatherings, and large events) the more that people observe others doing these activities and the more people perceived their own activities as riskier the prior week (for exercise and large events). It makes sense that these types of learning are less relevant for activities necessary for day-to-day living: food, errands, and school activities.

Conclusion. Even in contexts in which it is obvious that no one "knows" the appropriate course of action, we find that people rely on modeling behavior, looking to others for guidance. This social learning helps them make sense during uncertain times. As well, when norms for behavior are indeterminant, people use evaluations of their own experiences to assess the risk in uncertain activities, an experiential learning. Both are related to people engaging in more discretionary activities. Given these public behaviors were not necessarily sanctioned behaviors (as governmental and institutional mandates shifted), the uptick in these discretionary activities suggests a creeping risk tolerance for these activities that is not observed in more non-discretionary behaviors.

Materials and Methods

Full-time undergraduates living on campus or in the surrounding neighborhood qualified to participate in this study. Upon completion of Survey 1, participants received the project incentive, a Whoop, a wearable device and application.[4] There are 3 waves of 304 total participants because students moved back to campus at different times.[5] There are 1,962 observations for our pulse surveys because it includes Survey 1 as t-1. As Survey 1 is the original week, there is no data from the "previous week" for the Survey 1. Thus, the t-1 observation is "missing" for the data row that corresponds to the initial survey round. For

[4] Qualification details are in the Appendix.
[5] Wave 1 has 38 participants, Wave 2 has 144, and Wave 3 has 122.

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regressions focused on Survey 1, where there is no t-1 variable, there are 1,658 observations. As expected, the number of observations varies (if someone skipped a week but answered the following week's pulse). Survey materials, data, and analyses are available on the Open Science Framework (https://osf.io/9caqh/?view_only=8013bb5b0fcb43fea43558bef32e842e).[6]

Number of activities. In all surveys, participants reported the number of times they left their home to engage in 6 different categories of activities. During data analysis, we organized them into two higher-order categories, 1) non-discretionary activities, necessary for day-to-day living and 2) more discretionary activities, which were relatively less essential for day-to-day living, and were foregone by many during lockdown.

Discretionary activities outside of the home:

- *exercise*
- small in-person *social* gatherings (met friends, dated, saw significant other, etc.)
- large *events* or entertainment (house party, protest, rally, etc.)

Non-Discretionary activities outside of the home:

- eating and picking up *food* (from restaurants, cafeteria)
- running *errands* (entered drug store, curbside pick-up, etc.)
- and doing something for *school* (study group, enter school building for a lab)

Social Modeling. To examine social learning, participants reported how many people they saw taking part in those same activities. We asked,

[6] We posted a pre-registration but ran analyses based on inferences we made from initial analyses which were more appropriate for our data.

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> This past week, how many people did you see (or hear about) doing the following...We realize it may be difficult to estimate this but do your best! For instance, one friend may share their plans for the weekend and another friend may post to social media. In other situations, you might see things that your roommates/housemates/dorm-mates do. Or you might take a walk in your neighborhood and happen to observe people you don't know doing some of the things below.

They answered using six categories: (1) No One/Didn't Notice, (2) Very Few People (Less Than 10), (3) Few People (10 to 20), (4) Some People (20 to 40), Many People (40 to 60), (6) A Ton of People (More than 60). We named this variable *number of others observed*.

Perceived Risk of Past Behavior. To examine experiential learning, we measured people's perceived risk of their own past behavior. For Survey 1 and each pulse, after participants catalogued the three activities that put them most "at risk for exposure to COVID-19." Of course, these activities might include any mixture of the six categories (listing three exercise activities or two food and one social). Then, they rated any risk they associated with their engagement in each activity on a 100-point scale (participants had the option to enter "N/A" if they felt they did nothing that put them at risk). When reporting activities, people additionally reported the mitigating behaviors, if any, that they took (mask wearing, washing hands, etc.). Thus, we expect that their assessments of the risk associated with their past behaviors took their mitigating behaviors into account. We named this average numeric score *perceived risk*.

Methods. We ran a negative binomial regression as the outcome variables of interest, *number of activities*, are count variables.[7] We report results for two categories (discretionary and

[7] Often, researchers use a Poisson regression for estimating a regression where the dependent variable is a count variable. The Poisson regression assumes that the variance of Y is equal to the mean of Y. Estimates from the Poisson regression will be biased if the variance is greater than the mean, known as over dispersion. A Negative

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non-discretionary) with multiple activities for each category. In an attempt to adjust our significance threshold to account for multiple tests, we only report results for which $p < .01$.

Our two potential correlates of behavior in the current week are: 1) inferences from social learning, measured as Social Modeling: the number of people seen doing specific activities outside of the home during the prior week (*number of others observed*) and 2) inferences from experiential learning which we measure as Perceived Risk of Past Behavior: average self-assessment of one's own riskiest activities the prior week (*perceived risk*).

As participants' pattern of behavior at time (*t*) is highly correlated with their behavior in the previous week (time *t*-1), we include the number of activities in that same category at time *t*-1 as a control for all regressions predicting the number of activities reported at time (*t*). For example, the number of times people exercise at time *t*-1 is included as a control in the regression predicting the number of times people exercise at time *t*.

In order to make the coefficient of *number of others observed* interpretable on the categorical variable of activities reported, we take the mid-point of each range and summed the total within each category. Participants answered if they observe others outside their home to dine outdoors or indoors (e.g., cafeteria). We sum across specific activities for a total *number of others observed* doing activities related to food outside of the home. Specifically, the first range is 0 to 10 times. This range receives a score of 5, the midpoint between 0 and 10. The midpoint of the next range, 10 to 20, is 15. For example, if they report 0 people ordering delivery, very few people picking up takeout or dining outdoors, and a few people dining indoors, the score would be 0 + 5 + 5 + 15 = 25 for that week.

Binomial can account for over-dispersion in the data. In our case, there is over-dispersion in the outcome variable of interest, so we use a negative binomial regression.

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We estimate the relationship between participants' own activities, *number of others observed*, and *perceived risk* using:

$$Y_{it} = \beta_0 + \beta_1 Y_{it-} \ + \beta_2 O_{it-1} + \beta_3 R_{it-1} + \ \beta_4 X_i + \tau_t + \epsilon_{it}$$

where Y_{it} is the count of the number of times individual *i* did each activity in week *t*, Y_{it-1} is the one-week lag of the dependent variable, $O_{it-1}$is the number of others that individual *i* observed doing that activity in the previous week, $R_{it-1}X_i$ is the perceived risk of the most risky activities the individual did the prior week, X_i are time-invariant demographic controls including gender, political ideology, number of roommates, and class-year, τ_t is a week-of-sample fixed effect, and ϵ_{it} is an error term with mean zero. See Appendix Table 2 for heterogeneous effects.

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Appendix

Data

Some students attempted to take Survey 1 before they moved back to campus. In this case, they were unable to start the survey and asked to sign up to re-take it once they moved in. We exclude participants who did not complete at least 90 percent of Survey 1, observations for which an individual started the survey, did not complete it, and started a new Survey 1. We did not limit our sample to individuals who filled out all 7 pulse surveys. Individuals who took Survey 1, regardless of how many pulse surveys they took, were included in our sample. For example, someone who took Survey 1 and up to Pulse 3 would be included in the sample, as would someone who took Survey 1 and up to Pulse 10. If the participant completed multiple surveys in a single day, we kept either the later submission or the more complete survey (these were likely instances when they were not sure if their data had been submitted).

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Heterogeneous Treatment Effects

Methods. We also tested for heterogeneous treatment effects by gender, political affiliation, and class year using the same specification as above with interaction terms:

$$Y_{it} = \beta_0 + \beta_1 Y_{it-1} + \beta_2 R_{it-1} + \beta_3 R_{it-1} * G_i + \beta_4 R_{it-1} * P_i + \beta_5 R_{it-1} * C_i + \beta_6 O_{it-1} + \beta_7 O_{it-1} * G_i + \beta_8 O_{it-1} * P_i + \beta_9 O_{it-} * C_i + \beta_{10} X_i + \tau_t + \epsilon_{it}$$

where all terms are the same as in the first equation except G_i, which is a dummy variable equal to 1 if individual *i*'s self-reported gender is female, P_i, which is a categorical variable for political ideology on a scale of 1-7 with 1 being the most liberal and 7 being the most conservative, and C_i, which is a dummy variable for being a non-Senior. For clarity, we describe these results in prose and 1A-1F and report the discretionary activities in Figure 1.

Results. Our data also show a few heterogeneous effects. Male, students are influenced by the risk of their last week's activities for small gatherings. For small social gatherings, females show less association with experiential learning (note that they do report attending more social outings relative to men). Additionally, when interaction terms are added (Model 3), *number of others observed* and *politics* interacts on number of *large events* one attends. Specifically, conservative students' attendance at large events is less sensitive to how many people they saw at events in the prior week than politically liberal students.

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Pairwise Correlation

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Contracted Covid	1.000														
(2) Quarantined	.022 (.431)	1.000													
(3) Max Risk Perception (Current Week)	-.008 (.749)	.043* (0.104)	1.000												
(4) Max Risk Perception (Previous Week)	-.003 (.920)	.093*** (.001)	.679*** (.000)	1.000											
(5) Count of Food Related Outings (Previous Week)	.009 (.736)	.009 (.742)	.128*** (.000)	.169*** (.000)	1.000										
(6) Count of Exercise Related Outings (Previous Week)	-.027 (.307)	.005 (.855)	.209*** (.000)	.221*** (.000)	.218*** (.000)	1.000									
(7) Count of Social Related Outing (Previous Week)	.000 (.991)	.006 (.840)	.183*** (.000)	.253*** (.000)	.457*** (.000)	.281*** (.000)	1.000								
(8) Count of Event Related Outings (Previous Week)	.043* (.102)	.011 (.690)	.144*** (.000)	.199*** (.000)	.286*** (.000)	.132*** (.000)	.350*** (.000)	1.000							
(9) Count of Errand Related Outings (Previous Week)	-.007 (.779)	-.030 (.283)	.145*** (.000)	.173*** (.000)	.369*** (.000)	.217*** (.000)	.404*** (.000)	.207*** (.000)	1.000						
(10) Count of Social Related Outings (Previous Week)	-.009 (.731)	.011 (.691)	.039 (.110)	.101*** (.000)	.245*** (.000)	.036 (.143)	.235*** (.000)	.201*** (.000)	.249*** (.000)	1.000					
(11) Political Ideology (Liberal – Conservative)	-.031 (.205)	-.036 (.176)	-.075*** (.001)	-.080*** (.001)	.056** (.023)	.011 (.646)	-.046* (.060)	.126*** (.000)	-.068*** (.006)	-.069*** (.005)	1.000				
(12) Senior Level Student	.000 (.994)	-.002 (.927)	-.013 (.563)	-.024 (.328)	.028 (.258)	.026 (.291)	.084*** (.001)	-.021 (.401)	.067*** (.007)	-.088*** (.000)	-.118*** (.000)	1.000			
(13) Wave 1	-.016 (.498)	-.010 (.721)	.108*** (.000)	.113*** (.000)	-.007 (.765)	.022 (.365)	.016 (.507)	-.040* (.107)	.047* (.054)	-.042* (.090)	.027 (.240)	.017 (.457)	1.000		
(14) Wave 3	.048** (.047)	.082*** (.002)	-.040* (.076)	-.043* (.083)	.006 (.800)	-.022 (.378)	.040* (.106)	.042* (.087)	.037 (.135)	.063** (.010)	-.162*** (.000)	.119*** (.000)	-.312*** (.000)	1.000	
(15) Week	-.091*** (.000)	-.066** (.014)	-.179*** (.000)	-.189*** (.000)	-.188*** (.000)	-.208*** (.000)	-.230*** (.000)	-.124*** (.000)	-.320*** (.000)	-.122*** (.000)	.017 (.445)	.019 (.396)	-.174*** (.000)	.233*** (.000)	1.000

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

Appendix Table 1. Correlations between activity outings and likelihood of reporting having contracted COVID-19.

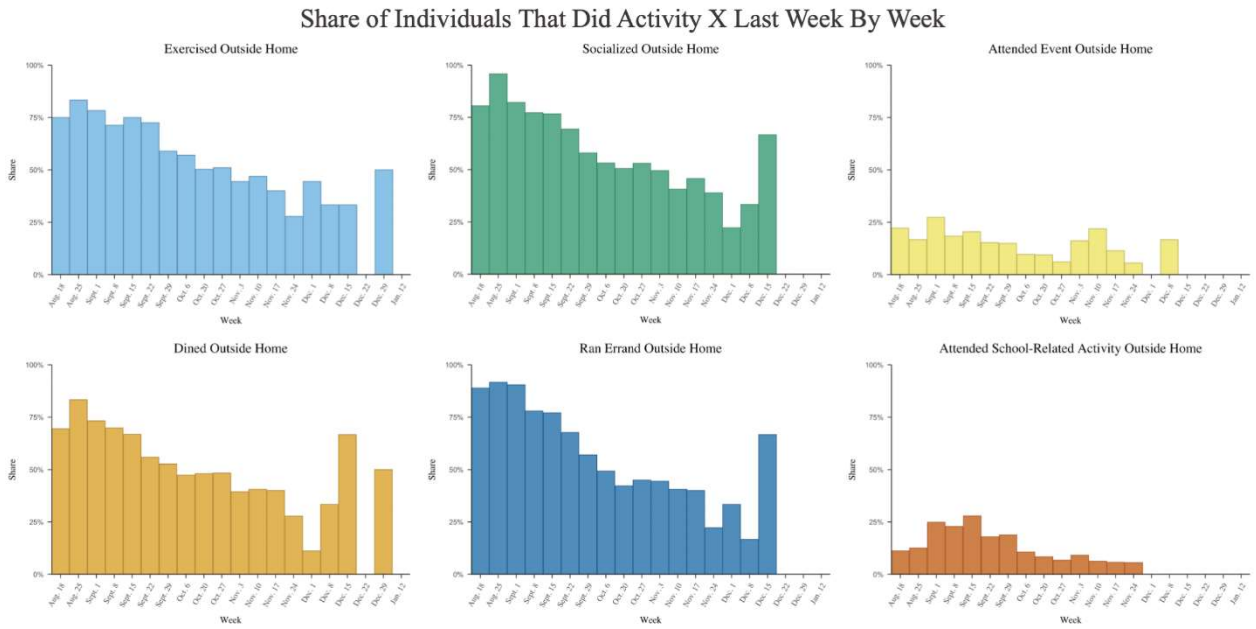
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	Model 1						Model 2						Model 3					
	Exercise Count	Social Count	Event Count	Food Count	Errand Count	School Count	Exercise Count	Social Count	Event Count	Food Count	Errand Count	School Count	Exercise Count	Social Count	Event Count	Food Count	Errand Count	School Count
Constant	.015	.024	-2.724***	-.446**	-.150	.044	-.319*	-.435**	-4.494***	-.799***	-.277	-.036	-.746**	-.915**	-6.299***	-.951**	-.422	-.922
	(.131)	(.135)	(.459)	(.165)	(.146)	(.386)	(.140)	(.157)	(.498)	(.178)	(.160)	(.420)	(.235)	(.307)	(.971)	(0.350)	(.247)	(.683)
Number of Outings T-1	.304***	.223***	.419***	.250***	.297***	.549***	.287***	.201***	.274***	.236***	.292***	.528***	.284***	.199***	.252***	.233***	.290***	.511***
	(.013)	(.013)	(.067)	(.017)	(.018)	(.069)	(.014)	(.013)	(.057)	(.017)	(.018)	(.074)	(.014)	(.013)	(.059)	(.017)	(.018)	(.073)
Female	.045	.196***	.114	.250***	.161**	.344*	.021	.170**	.001	.227***	.138*	.342*	.260	.396	.754	.269	.122	.972**
	(.049)	(.058)	(.188)	(.066)	(.058)	(.171)	(.048)	(.058)	(.176)	(.066)	(.058)	(.170)	(.139)	(.207)	(.476)	(.190)	(.149)	(.377)
# Roommates	.010	.012	.066	.048**	-.006	-.118**	.004	.005	.070	.044**	-.005	-.126**	.001	.008	.076	.046**	-.005	-.132**
	(.013)	(.015)	(.044)	(.016)	(.014)	(.041)	(.012)	(.015)	(.043)	(.016)	(.014)	(.042)	(.012)	(.015)	(.043)	(.016)	(.014)	(.040)
Politics: Liberal (1) to Conservative (7)	-.006	.005	.324***	.000	-.032	-.089	-.014	-.002	.366***	-.001	-.035	-.109	.066	.078	.718***	.027	-.033	-.011
	(.018)	(.022)	(.058)	(.025)	(.022)	(.062)	(.018)	(.022)	(.058)	(.025)	(.022)	(.062)	(.050)	(.080)	(.166)	(.084)	(.055)	(.132)
1[Class= Senior]	.027	.234***	.193	.116	.210**	-.115	.041	.247***	.218	.126	.217***	-.084	.231	.507*	.633	.268	.451**	.436
	(.055)	(.069)	(.194)	(.078)	(.065)	(.195)	(.054)	(.068)	(.174)	(.077)	(.064)	(.190)	(.138)	(.225)	(.503)	(.209)	(.156)	(.377)
week	-.030**	-.050***	-.055	-.023	-.052***	-.204***	-.025*	-.045***	-.035	-.018	-.050***	-.206***	-.026*	-.045***	-.037	-.019	-.050***	-.209***
	(.011)	(.010)	(.034)	(.012)	(.011)	(.036)	(.011)	(.010)	(.036)	(.012)	(.011)	(.035)	(.011)	(.010)	(.032)	(.012)	(.011)	(.032)
1[Wave=1]	.049	.114	-.496	.024	.155*	.174	.033	.112	-.566	.015	.137	.272	.035	.118	-.486	.014	.137	.229
	(.063)	(.088)	(.282)	(.098)	(.077)	(.282)	(.064)	(.087)	(.306)	(.098)	(.077)	(.283)	(.063)	(.088)	(.299)	(.098)	(.078)	(.273)
1[Wave=3]	-.009	.096	.095	.004	.133*	.547**	.015	.100	.206	.014	.131*	.594**	.012	.083	.253	.015	.135*	.658***
	(.055)	(.063)	(.205)	(.073)	(.063)	(.192)	(.054)	(.062)	(.184)	(.073)	(.062)	(.186)	(.054)	(.061)	(.187)	(.073)	(.063)	(.188)
Number of Others Observed T-1							.001**	.001***	.006***	.003**	.000	.005**	.003**	.003***	.017***	.006	.001	.005
							(.000)	(.000)	(.002)	(.001)	(.000)	(.002)	(.001)	(.001)	(0.005)	(.004)	(.001)	(.006)
Risk Perception Max. T-1							.005***	.002*	.020***	.003**	.002	-.001	.008**	.001	.036**	.003	.001	.019
							(.001)	(.001)	(.003)	(.001)	(.001)	(.003)	(.003)	(.004)	(.012)	(.004)	(.004)	(.012)
Number of Others Observed T-1 * Female													-.001	.000	-.002	.002	.000	-.002
													(.001)	(.001)	(.003)	(.002)	(.000)	(.004)
Number of Others Observed T-1 * Politics													-.000	-.000*	-.003**	-.001	-.000	.001
													(.000)	(.000)	(.001)	(.001)	(.000)	(.001)
Number of Others Observed T-1 (x10) * Class													-.001	-.001	-.002	-.003	-.001	-.002
													(.001)	(.001)	(.003)	(.002)	(.000)	(.004)
Risk Perception Max. T - 1 * Female													-.003	-.007**	-.010	-.004	.000	-.013
													(.002)	(.002)	(.006)	(.002)	(.002)	(.007)
Risk Perception Max. T - 1 * Politics													-.001	.002	-.002	.000	.001	-.002
													(.001)	(.001)	(.002)	(.001)	(.001)	(.002)
Risk Perception Max. T-1 * 1[Class= Senior]													-.000	-.002	-.006	.001	-.002	-.010
													(.002)	(.002)	(.006)	(.002)	(.002)	(.007)
lnalpha	-1.065***	-.432***	1.859***	-.341**	-1.218***	1.692***	-1.141***	-.486***	1.570***	-.369***	-1.225***	1.675***	-1.159***	-.529***	1.533***	-.388***	-1.231***	1.640***
	(.175)	(.099)	(.149)	(.107)	(.189)	(.128)	(.179)	(.102)	(.144)	(.108)	(.189)	(.127)	(.181)	(.105)	(.145)	(.111)	(.191)	(.129)
Observations	1638	1638	1638	1638	1638	1638	1637	1634	1634	1637	1634	1634	1637	1634	1634	1637	1634	1634

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

Appendix Table 2. *Number of activities* reported in the current week (Discretionary: Exercise, Social, Event; Non-Discretionary: Food, Errand, School) as predicted by the *number of others observed* and *perceived risk* both in the prior week, controlling for the number of outings in the previous week and demographics

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Appendix Figure 1A-1F. Percentage of participants reporting an activity at least once the previous week. The denominator varies by week and is the total number of participants who responded to the survey that week. From upper left clockwise,
Discretionary: Exercise, Social, Event; Non-Discretionary: Food, Errand, School.

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Robustness checks

Additionally, we conduct two robustness checks, starting with the parameters of fewer researcher degrees of freedom. Since participating in 7 pulse surveys was all that was expected or required of students, our first robustness check removes any observations past pulse 7, to remove observations from students who might have been especially conscientious. Results are generally consistent with our main models. *Number of others observed* is positively related to attending events, small group gatherings, and exercise (albeit the last category only at $p<.05$, given the lower power with fewer observations). *Perceived risk* is positively related to exercise and events. Thus, the results from this robustness check largely mirror the main results using the entire dataset.

For the second robustness check, we use all the data but parse food and exercise categories into more versus less discretionary categories. We consider food activities outside of the house such that *indoor* dining to be more discretionary, whether it was alone or with others. We consider activities that took place *outdoors*, either by oneself or with others as less discretionary.[8] For exercise activities, exercising *indoors,* either by oneself or with others as well as *outdoors and with others* is considered more discretionary. Exercising *outdoors and by oneself* is considered less discretionary. Categorizing these exercise and food activity variables into more versus less discretionary also required a similar adjustment of the social learning independent variable. For example, more discretionary exercise activities are only predicted by number of others observed engaging in more discretionary exercise (not by number of others observed engaging in less discretionary exercise).

In the main effects models, *discretionary exercise* and *discretionary food* are significantly and positively related to *number of others observed*, these results hold when interaction terms are added, though

[8] Considering some students lived in dorm rooms, outdoor dining was their only viable option for eating, making it less discretionary than the other options.

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the results for *discretionary food* drop to $p<.05$. Thus, results suggest the creeping risk tolerated in discretionary exercise and discretionary food activities associated with social learning. *Discretionary exercise* and *discretionary food* are also significantly and positively related to *risk of last week's activities,* though when interaction terms are added, results only remain significant for *discretionary exercise.* The conservative interpretation is that discretionary exercise activities also creep up within an experiential learning paradigm, but discretionary food activities do not.

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