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COVID-19 RISK (MIS)PERCEPTIONS

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COVID-19 Risk (Mis)Perceptions[*]

Xavier Dufour-Simard[†] and Pierre-Carl Michaud[‡]

Abstract/Résumé

Using a unique large-scale survey repeated over a period of 18 weeks during the Omicron variant wave of early 2022, we study how subjective risk perceptions line up with objective risks across various socio-economic groups in Quebec, Canada. We find that perceptions and infection estimates follow surprisingly similar trends in the aggregate but vary significantly across groups. We associate misperceptions with characteristics such as age, vaccination status and sector of employment. We discuss various implications of these results in terms of prevention and of the effectiveness of policy aimed at reducing the risk of infection through information and education.

En utilisant une enquête de grande envergure répétée sur une période de 18 semaines pendant la vague du variant Omicron au début de 2022, nous étudions comment les perceptions subjectives des risques s'alignent avec les risques objectifs au sein de divers groupes socio-économiques au Québec, Canada. Nous constatons que, globalement, les perceptions et les estimations des infections suivent des tendances étonnamment similaires, mais qu'elles varient significativement d'un groupe à l'autre. Nous associons ces distorsions de perception à des caractéristiques telles que l'âge, le statut vaccinal et le secteur d'emploi. Nous discutons des diverses implications de ces résultats en termes de prévention et d'efficacité des politiques visant à réduire le risque d'infection par l'information et l'éducation.

Keywords/Mots-clés: risk perception, COVID-19, prevention / Perception des risques, COVID-19, prévention

JEL Codes/Codes JEL: I12, I18, I19

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1 Introduction

In November 2021, a new variant of the Coronavirus emerged. Compared to previous variants, the Omicron variant was more contagious and led to an impressive wave of COVID-19 cases in early 2022. In many parts of the world, the PCR testing infrastructure could not meet the demand for tests and several countries rapidly moved toward self-administered tests. In Canada, several provinces, including Quebec, had shortages of such tests and the surveillance system of the disease collapsed in early 2022. It was impossible at that moment to know the state of the pandemic. Given that hospitalizations typically follow infections with a lag, this collapse impaired planning in the healthcare system for what was to come. Together with researchers from other universities in Quebec, we embarked on a data collection effort to track the number of COVID-19 cases using survey methods. Over the course of 18 weeks, we surveyed 3,000 adult respondents each week in the province of Quebec and collected information on COVID-19 infections and risk perceptions, as well as other variables such as vaccination status. While the pandemic is behind us, new pandemics could occur and studying risk perceptions may help us design more effective interventions.

These data provide a unique opportunity to investigate how risk perceptions compare to actual risks in a broad cross-section of the population and to follow how these risk (mis)perceptions evolve over the course of a COVID-19 wave. Risk perceptions play an important role in determining self-protection efforts, including vaccination and support of non-pharmaceutical interventions. A growing literature explores subjective risk perceptions associated with COVID-19. Hong et al. (2023) note that risk perceptions are strongly correlated with actual risk, while Bundorf et al. (2021) find that infection risk perceptions map well to observed differences across socio-economic groups despite a generalized overestimation of the risk. Women generally perceive a higher risk (Bughin et al., 2021; Bundorf et al., 2021), and take more preventive measures than men (Cipolletta et al., 2022; Fan et al., 2020). Perceived vulnerability to infection is found to be much higher in younger people (Bordalo et al., 2020; Ladapo et al., 2022; Rosi et al., 2021). Comparing the probability and severity of infection, Bundorf et al. (2021) and Rosi et al. (2021) find that older age groups perceive a lower risk of infection but a higher risk of a severe infection.

Higher income and education have been associated with higher risk perception (Bughin et al., 2021; Cipolletta et al., 2022) and intent to vaccinate (Leigh et al., 2022), whereas lower educated groups are more likely to agree with erroneous statements regarding the risks associated with COVID-19 (Bhuiya et al., 2021). Misinterpretation of statistics has also been shown by Joslyn et al. (2021) to have an effect on risk perception. The literature on vaccine acceptance finds that intent to vaccinate is higher among older people, men, the urban population, and individuals who have higher risk perceptions (Cipolletta et al., 2022; Joshi, Ashish and Kaur, Mahima and Kaur, Ritika and Grover, Ashoo and Nash, Denis and El-Mohandes, Ayman, 2021). Healthcare workers have been found to have high risk perceptions and engage in more protective behaviors (Cipolletta et al., 2022), including a higher than average intent to vaccinate (Joshi, Ashish and Kaur, Mahima and Kaur, Ritika and Grover, Ashoo and Nash, Denis and El-Mohandes, Ayman, 2021). Teachers have also been identified as a group being pessimistic about infection risk while having a higher intent to vaccinate (Weinert et al., 2021). This pessimism occurs despite results suggesting that children to staff contamination remained low in schools during the pandemic (Ismail et al., 2021).

Very little longitudinal evidence on risk perception has been produced despite the findings of Wang et al. (2021) and Norton et al. (2023) that suggest socio-economic groups face time-varying risks over different COVID-19 waves. Additionally, most studies rely on datasets that have been collected in 2020 or 2021, prior to or in the early stage of vaccine rollout. To the best of our knowledge, no study has been done on how perceptions developed as individuals got more comfortable with the risk posed by COVID-19. The literature identifies characteristics that predict differences in risk perception, but no study has exploited data large enough to allow a direct estimation of the objective risk faced by such groups.

We report three key findings. First, we find that risk perceptions in the aggregate match objective risk measures surprisingly well over time. Second, we find significant differences between objective and subjective risks in specific socio-economic groups. We associate increasing risk assessment biases with age groups (3.4 to 9.8 percentage points over-estimation), an underestimation of risk by the unvaccinated (6.5 pp), a negative risk assessment bias for households with children (3.3 pp) and an overestimation of risk for workers in the education sector (4.8 pp). Third, we find that the relative misperceptions across groups are very persistent and do not show evidence of convergence over the course of the Omicron wave.

The paper is structured as follows. We first describe the data in section 2. We then present in section 3 the methods we use to compare subjective and objective COVID-19 risks in the population. We report results in section 4 and discuss their implication in section 5.

2 The Survey

The survey was conducted online in the first half of 2022 by the *Centre interuniversitaire de recherche en analyse des organisations* (CIRANO) via the *Leger Opinion* (LEO) survey panel. The survey was available to Quebec residents in French and English and took an average of 6 minutes and 14seconds to complete. It was available from January 13th to May 17th 2022, covering one of the largest waves of COVID-19 infections the province of Quebec had to face.[1]

2.1 Data Collection

The collection took place over 6-day windows for 18 consecutive weeks (waves). The first wave was collected between January 13 and 18, the second between the 20th and 25th and so forth until the 18th wave, which was collected between the 12th and 17th of May. Roughly 3,000 participants were surveyed each week, resulting in a total of 54,155 respondents aged 18 and over. We use Statistics Canada's 2016 Census to make the sample representative of the adult population of Quebec and sample weights are used throughout for statistical analysis.

2.2 COVID-19 Objective Risk Measurement

The objective risk of infection faced by respondents can be estimated from the survey using two different measures. The first one relies on a question asking participants if in the last 7 days they have experienced any symptoms that could be associated with COVID-19. The survey provided a list of COVID-19 symptoms[2] recognized by the Government of Quebec as COVID-19 symptoms. This indicator is used to estimate the presence of potential COVID-19 infections among respondents in a context where other means of diagnosis were mostly not accessible.

[1] The data used for this study is available at https://github.com/pcmichaud/EnqueteCovid

[2] The listed symptoms included 1) Fever, 2) General symptoms (loss of smell, loss of taste, major fatigue, major loss of appetite, general muscle pain, headache, night sweats), 3) Respiratory symptoms (cough, shortness of breath, difficulty breathing, sore throat, runny nose, nasal congestion of unknown cause), 4) Gastrointestinal symptoms (nausea, vomiting, diarrhea, stomach aches).

Access to PCR tests was constrained in Quebec on January 4th because of high demand, meaning the general population had to rely on rapid tests for diagnosis, which were in very limited supply in early 2022. An average of 13.1% of our sample reports having at least one COVID-19 symptom in the last 7 days. This symptoms measure can be compared to a subjective expectation measure to assess correspondence.

The second measure looks at testing, despite difficulty with access. The survey asks respondents if they tested positive for COVID-19 in the past 7 days. Possible answers are *(1) Yes, (2) No, (3) No test results, but I believe I have contracted it (self diagnosis based on my symptoms over the past 7 days)*. This variable is used as a secondary measure of the prevalence of the virus among our sample. Because rapid tests were hard to come by during the early stages of data collection we decided to consider self-diagnosis as confirmed cases of COVID-19. Self-diagnoses account for a quarter of the total infections reported using this measure. Including them in our definition increases the average infection rate from 2.94% (test results) to 4.01% (test results and self-diagnosis).

Each of these measures has drawbacks. The symptoms measure is limited by the fact that symptoms associated with COVID-19 can also be associated with other conditions like flu, meaning we could be over-estimating actual COVID-19 infections.[3] On the other hand, asymptomatic infections are not accounted for by this measure, meaning we could be under-estimating actual COVID-19 infections. The diagnosis measure is limited by the collapse of the testing infrastructure. Without tests, participants cannot observe their infection status. Rapid tests were hard to come by and at some point more easily available to certain demograph-

[3] The most common symptoms identified are respiratory symptoms (7.8% of sample), followed by general symptoms (5.1%), gastrointestinal symptoms (4.1%) and fevers (1.8%). The relative importance of each group of symptoms remained constant over the 18 weeks of data collection.

ics (older people, healthcare workers, certain regions...), which could lead to an uneven reporting of diagnosis. We try to alleviate this problem by considering self-diagnosis, but self-diagnosing is an arbitrary decision that could be hard to make when experiencing few/weak symptoms. This is especially relevant considering that symptoms are known to be weaker with the Omicron variant when vaccinated (Chenchula et al., 2022).

We show in Figure 1 the evolution of the two risk measures over time, normalizing levels to 1 in the week of February 3rd 2022. We also compare them with other official estimates.[4] Both of our survey-based objective risk measures follow similar trends and match quite well the trend from official statistics.

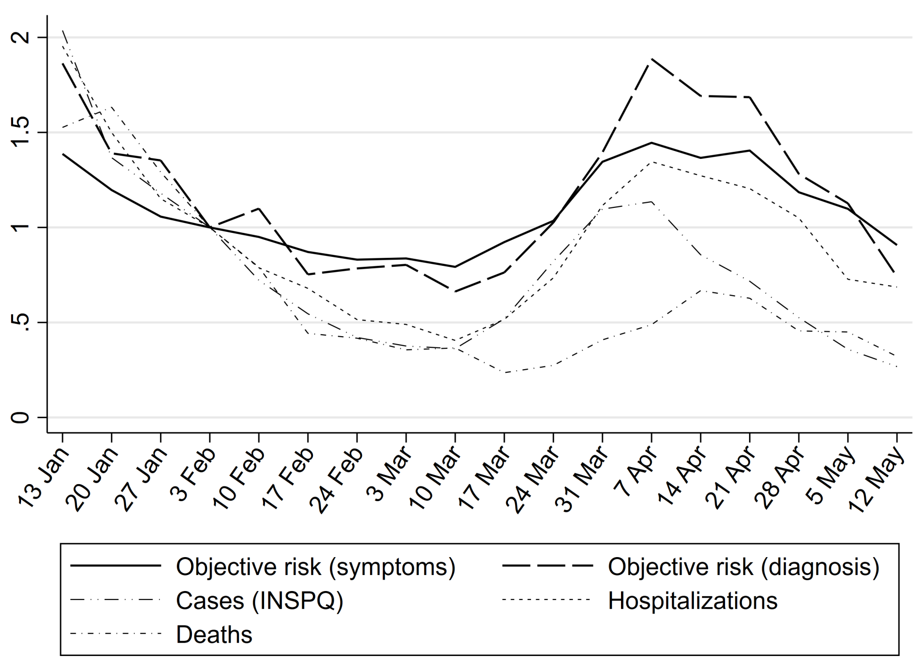

Figure 1: **Comparison of Objective Risk Measures**: The figure compares our 2 objective risk measures with different data from the INSPQ over the same period.

[4]The *Institut national de santé publique du Québec* (INSPQ) produces a measure based on PCR tests only available to a sub-population including healthcare workers; see https://www.inspq.qc.ca/covid-19/donnees/methodologie for more details.

2.3 COVID-19 Subjective Risk Measurement

Regarding the subjective risk measurement, the participants to the weekly survey were asked *On a scale of 0 to 100, how likely do you think it is that you will develop symptoms associated with COVID-19 in the next 7 days? Mark 0 if you have no chance of developing symptoms and 100 if it is certain that you will develop symptoms*. This question asks participants to formulate a probabilistic expectation of their risk of infection. The average subjective probability is 13.5%, which compares favorably to the average objective symptoms risk of 13.1%. Participants that declared having COVID-19 symptoms, had tested positive, or had self-diagnosed at the time of answering the survey are not included when measuring this expectation.

In Figure 2, we report the distribution of subjective risk assessments. About 45% of participants estimate their risk at 0, which could be the consequence of excess optimism (Garfin et al., 2021) or an underestimation of the risk of (re)infection. Interestingly, 11.9% of the sample estimates their probability of infection at 50% which could reflect epistemic uncertainty (de Bruin et al., 2000).

Figure 3 presents the evolution of the virus' prevalence over the 18 weeks of collection, as measured by our two objective variables, and compares it to the weekly subjective risk perception. Because the risk perception (which was asked for the next 7 days) has to be compared to objective risk measures based on the 7 previous days, the subjective estimates are shifted forward a week, resulting in a week of data being lost in the process.

We find that the three risk measures follow a surprisingly similar trend, suggesting infection expectations are in line with objective risk in the aggregate. Interestingly, subjective estimates seem to react late to the increase in risk that happens in late March / early April. For the remainder of our analysis, we assume that the

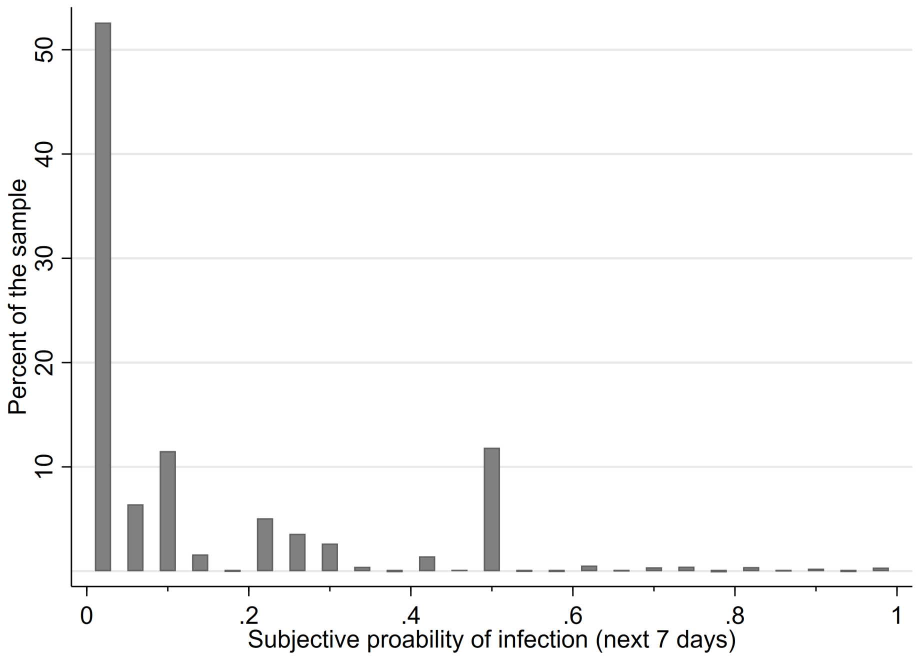

Figure 2: **Distribution of Subjective Risk Measure**: Weighted histogram of the distribution of the subjective risk variable which captures the subjective probability of developing COVID-19 symptoms in the next 7 days. All waves are pooled to produce this graph.

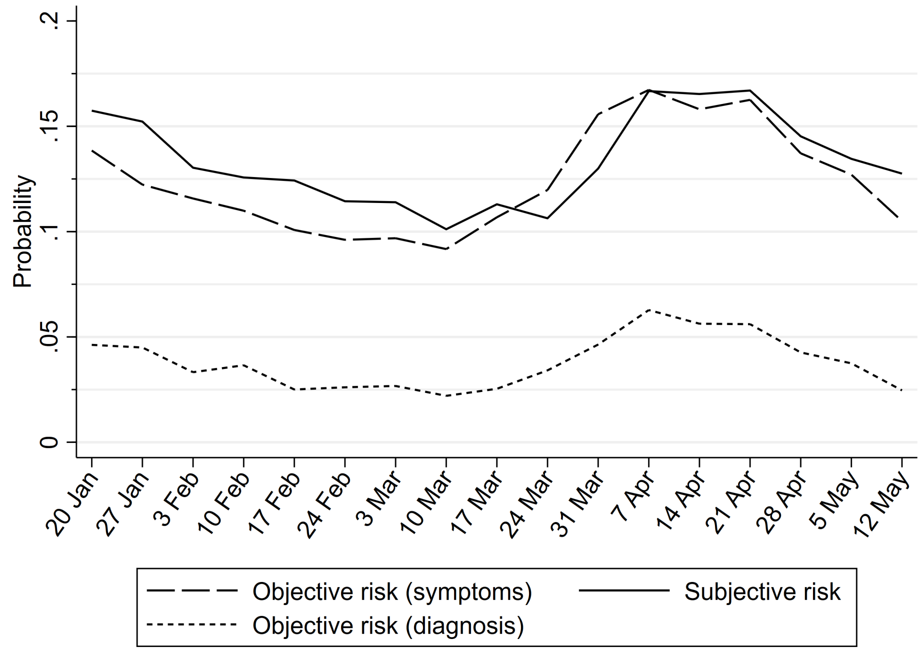

Figure 3: **Trends in Objective and Subjective Infection Risks**: The figure reports the weighted average subjective probability of having symptoms associated with COVID-19 in the next 7 days (subjective) and the weighted fraction of respondents with a) symptoms associated with COVID-19 (long-dashed) and b) a (self-)diagnosis (short-dashed) in the previous week. The dates correspond to the first day of the 6-day collection of each wave. Subjective estimates are shifted a week forward to facilitate comparison.

prevalence of the virus is best represented by the objective risk measure derived from symptoms because it matches the subjective assessment question (which asks for symptoms), allowing for a more direct comparison of the two.

2.4 Composition of Sample

Descriptive statistics of the sample are presented in Table 1. We use weights derived to match the Canadian Census to produce these statistics. We observe in our sample that 94.5% of women and 93.3% of men are vaccinated. Vaccination rates increase with education, household income and age. In terms of occupations, stayat-home/unemployed participants have the lowest vaccination rate (85.5%), while education (94.6%), public administration (95.1%) and healthcare workers (96.1%) have the highest rates among working participants. Vaccination coverage is found to be higher in men, older people, more educated people, teachers, and healthcare workers; it mostly corresponds to the vaccination intent literature (Cipolletta et al., 2022; Leigh et al., 2022; Joshi, Ashish and Kaur, Mahima and Kaur, Ritika and Grover, Ashoo and Nash, Denis and El-Mohandes, Ayman, 2021; Weinert et al., 2021).

3 Methods

Our objective is to assess whether subjective risk expectations match objective risks, in particular among subgroups. First, we focus on the cross-sectional dimension by pooling all waves. The objective status of infection for participant i is defined by the variable Y_i, which equals 1 if infected and 0 otherwise. Participants are considered infected upon the presence of self-assessed symptoms (the symptoms measure). We model the Bernoulli distribution of this binary variable as a function of a set of characteristics X. We use the subscript o to refer to the objective nature of the risk measure. The expectation of this risk measure as a function of X yields a measure of the probability of being infected given characteristics X:

$$\mathbb{E}_o(Y_i|X_i) = 1 * \Pr(Y_i = 1|X_i) + 0 * \Pr(Y_i = 0|X_i) = \Pr(Y_i = 1|X_i) \tag{1}$$

We model this probability using a probit model (2), where Φ is the cumulative distribution function of the standard normal distribution,

		% of sample
Sex	Woman	51.2
	Man	48.2
Age	18-29	17.3
	30-39	15.4
	40-49	17.2
	50-59	16.8
	60-69	20.5
	70+	12.9
Household composition	With kid(s)	25
Region of residence	Montreal	50
	Quebec city	10
	Other regions	40
Household income	<20k	6.2
	20 - <40k	14.1
	40 - <60k	17.2
	60 - <80k	14.1
	80 - <100k	13.1
	$\geq$ 100k	24.8
Education	Elementary	0.1
	Secondary	29.7
	CEGEP	43.7
	University	25.1
Sector / Occupation	Agriculture & Construction	4.7
	Finance & Professional Services	15.9
	Public Administration	8.4
	Retail & Services	8.1
	Manufacturing & Transportation	8.1
	Education	4.4
	Healthcare	6.3
	Retired	29.1
	Student	7.1
	At home/Unemployed	7.1
Vaccination	At least one dose	92.5
	Not vaccinated	6
	No answer	1.5

N = 54,155; n per wave $\in$ [3,000 , 3,027].

Table 1: **Descriptive Statistics**: weighted using Census weights provided by Leger. All waves of the survey are pooled to produce these statistics.

$$P_o(X_i) = Pr(Y_i = 1|X_i) = \Phi(X_i\beta_o). \tag{2}$$

All characteristics in X_i are categorical variables. Hence, the effect of turning characteristic j to 1 is given by the difference in predicted probabilities (marginal effect) setting $X_j = 1$ and $X_j = 0$. Denote by $\Delta_j P_o(X_i)$ this marginal effect.

Every participant has an estimation of his personal risk of developing symptoms, defined by the expression $\mathbb{E}_s[Y_i|X_i]$, where index s refers to the subjective nature of the measure. We hypothesize that this estimation comes from a linear single index model with explanatory variables X_i and a vector of β_s coefficients.

$$\mathbb{E}_s[Y_i|X_i] = P_s(X_i) = X_i\beta_s. \tag{3}$$

Our survey asked participants to provide a probabilistic expectation of their risk of infection, which we denote P_i. This expectation can take any value between 0 and 1; hence we define a linear regression model such that

$$P_i = X_i\beta_s + \epsilon_i \tag{4}$$

The parameters β_s are estimated by OLS. Both regressions use the same vector of j categorical explanatory variables. This structure implies that results are expressed and should be interpreted in relation to a reference group. Respective coefficients and marginal effects of a variable $X_j \in \{0,1\}$ reflect changes in risks associated with the socio-economic group having characteristic $X_j = 1$ relative to the group having $X_j = 0$. A positive result indicates that the group faces a higher risk than the reference group.

We can test directly whether differences in risks in the population are correctly perceived. Under the null hypothesis that these differences are correctly perceived, the difference between a subjective coefficient ($\beta_{s,j}$) and the corresponding marginal effect ($\Delta_j P_o(X_i)$) should be zero. Otherwise, there is bias in the relative risk assessments. Hence, we compute the distance

$$RAB_j = \beta_{s,j} - \Delta_j P_o(X_i). \tag{5}$$

When interpreting this difference, it cannot be assumed that the group having $X_j = 1$ is biased, only that a bias is captured in the difference in risk between those with characteristic j and those in the reference group. A positive RAB implies an overestimation of risk relative to the reference group, while a negative RAB implies an underestimation. Given that both estimates are normally distributed, the validity of the null hypothesis can be tested by a simple t-statistic. Given that these are estimated on overlapping datasets, we use a conditional mixed process estimator that accounts for any potential correlation of error terms between regressions and to compute confidence intervals for differences in coefficients (Roodman, 2007).

3.1 Explanatory Variables

The vector of explanatory variables includes socio-economic characteristics of the participant. Variables include sex (reference: man); age group in 10-year increments, except for the youngest and the oldest (ref: 18-29 y.o.); household income in \$20k increments (ref: \$60-80k); education level (ref: CEGEP); household composition[5] (ref: single person HH); region of residence (ref: Montreal); vaccination

[5]Household composition is measured as the total number of people residing in the household, not reported in Table 1, and a binary variable indicating the presence of a child.

status[6] (ref: unvaccinated); and sector of employment / occupation[7] (ref: Finance & Professional Services[8]). We also include week fixed effects to control for possible trends in the data.

4 Results

4.1 Cross-Sectional Differences

The results of three models are presented in Table 2. The first model (1) presents the OLS regression on subjective risk assessments, while model (2) presents marginal effects of the objective risk regression. Both present results in percentage points (pp) in the table to facilitate interpretation. The third model (3) computes the difference between models (1) and (2), which we call the risk assessment bias (RAB). The mean of the dependent variables ($\bar{P} = 13.5\%$ and $\bar{Y} = 13.1\%$) help put the following results in perspective.

Using the 18 to 29 years old as reference, Figure 4[9] shows a RAB that increases with age from 3.4 pp for the 30-39 y.o. to 9.6 pp for the 70 years old and above. We see that this bias comes from older people being associated with a much lower risk of reporting symptoms (objective risk) – going from -3.9 pp for the 30 to 39 y.o. to -14.3 pp for the 70+ – that does not match the reduction in perceived risk of devel-

[6] The vaccination status considers individuals vaccinated if they have received at least one dose of a COVID-19 vaccine

[7] The sectors are: 1) Agriculture, forestry, mining, exploitation and construction, 2) Finance, insurance, professional services, administration, real estate and management, 3) Public administration and utilities, 4) Retail, information and culture, arts and entertainment, accommodation and food services, 5) Manufacturing, wholesale, transportation and warehousing, 6) Educational services, 7) Healthcare, social assistance, 8) Retired, 9) Student, 10) At home/Unemployed.

[8] This sector represents the largest sector of employment. 33% of the sector worked in person, 41% remotely and the rest in hybrid. This corresponds to the lowest rate of in-person workers among the sectors considered.

[9] Only statistically significant relative biases are presented in Figure 4; Table 2 shows all differences.

oping symptoms (-0.5 pp for the 30-39 y.o. to -4.6 pp for the 70+). These results indicate that age groups are associated with increasingly different risk measures. This contrasts with the work of Bundorf et al. (2021) that finds that age was not predictive of differences in perceived risk early in the pandemic, but is in line with that of Bordalo et al. (2020), Ladapo et al. (2022) and Rosi et al. (2021) who find that younger age groups perceive a higher risk of infection.

Vaccinated participants are associated with a positive RAB of 6.5 pp. Model (1) suggests that most of this bias is the result of unvaccinated participants perceiving a much lower risk of developing symptoms (8.8 pp below that of the vaccinated). Interestingly, vaccination is associated with an increased objective risk (2.3 pp). This could be the result of higher risk taking among the vaccinated, despite Agrawal et al. (2022) finding no evidence of moral hazard following vaccination in the United States.

Living with a child (under 18) is associated with a negative RAB of 3.3 pp. This comes from a more important difference in objective (4.4 pp) than in subjective risk (1.1 pp). This result suggests that people living with children could have underestimated the added risk their child represents.

Compared to workers in Finance & Professional Services, healthcare workers are associated with higher subjective (3.3 pp) and objective (3 pp) risks, for which the difference (RAB) is not significant. On the other hand, education workers are associated with a RAB of 4.8 pp. This result is mainly driven by a subjective risk increase (7.3 pp) that is not matched by the objective risk (2.5 pp), suggesting an important overestimation of risk by the group. Finding higher levels of subjective risks among the healthcare and education sectors is in line with results presented in Cipolletta et al. (2022) and Weinert et al. (2021), and the higher levels of objective risk are in line with the more intensive human contact we expect in these sectors.

Falco et al. (2021) find that the risk of infection at work is associated with emotional exhaustion, which can be attenuated by specific measures in the work environment (i.e., communication, participation in decision making, fatigue management). Our results add to theirs by suggesting that this exhaustion could be heterogeneous among sectors of employment.

Overall, these results indicate that expectations only seem to be accurate in the aggregate. Once decomposed among socio-economic groups, many significant and sizeable (relative) biases appear. This is important since behavior is likely influenced more by subjective expectations of the risk than by the objective risk itself. We develop the implications of these results in Section 5.

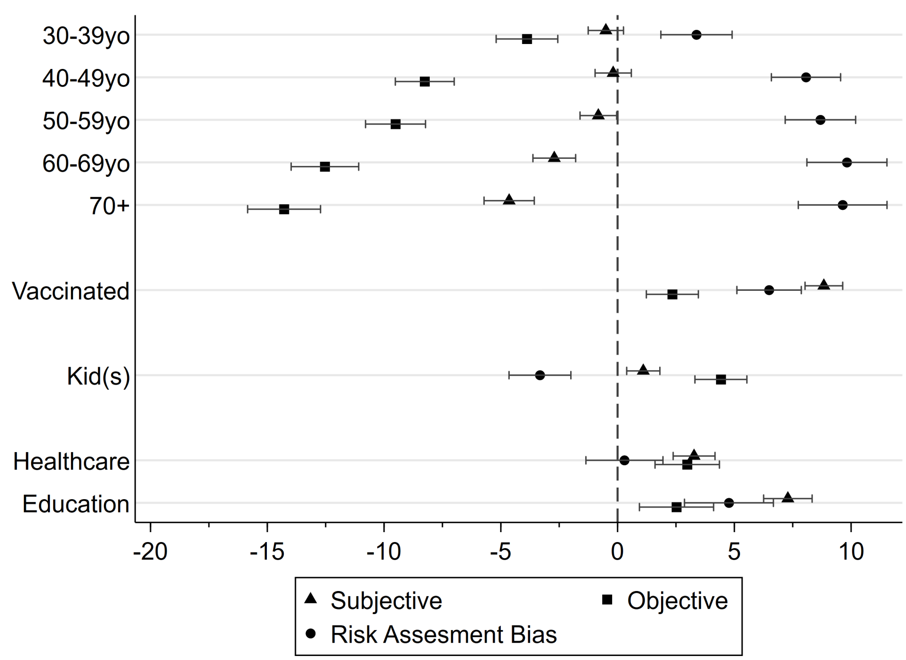

Figure 4: **Regression results**: This figure summarizes the main relations identified by our analysis. Results are interpretable as percentage point differences between a group and its reference.

		(1) Subjective Risk		(2) Objective Risk		(3) Risk Assessment Bias	
Variable		Coefficient	Std. Error	Marginal Effect	Std. Error	Coefficient	Std. Error
Sex (ref.: Man)	Woman	0.2484	0.1987	1.4824***	0.3136	−1.2340***	0.3725
Age (ref.: 18-29)	30-39	−0.5021	0.3858	−3.8806***	0.6734	3.3785***	0.7782
	40-49	−0.1882	0.3957	−8.2566***	0.6430	8.0684***	0.7562
	50-59	−0.8239*	0.4002	−9.5089***	0.6552	8.6850***	0.7696
	60-69	−2.7106***	0.4666	−12.5316***	0.7381	9.8209***	0.8745
	70+	−4.6431***	0.5485	−14.2809***	0.7962	9.6378***	0.9693
HH income (ref.: 60 - <80k)	<20k	−0.3336	0.4833	−0.5890	0.7800	0.2553	0.9202
	20 - <40k	−0.7270*	0.3534	−1.2173*	0.5834	0.4903	0.6838
	40 - <60k	0.2467	0.3269	−0.7278	0.5375	0.9745	0.6308
	80 - <100k	0.7059*	0.3499	−1.1522*	0.5551	1.8581**	0.6580
	≥100k	−0.3664	0.3170	−2.2574***	0.4912	1.8910**	0.5859
Education (ref.: CEGEP)	Elementary	1.1033	1.0284	1.6526	1.7115	−0.5493	2.0026
	Secondary	0.0952	0.2320	−1.0429**	0.3600	1.1381**	0.4297
	University	−0.0713	0.2480	1.5812***	0.3941	−1.6525***	0.4670
HH composition (ref.: 1 person)	With kid(s)	1.1008**	0.3626	4.4249***	0.5678	−3.3242***	0.6759
	2 persons	0.2103	0.2664	0.1057	0.4373	0.1046	0.5135
	3 persons	−0.1286	0.3933	1.1415	0.6196	−1.2701	0.7358
	4 persons	0.4456	0.4487	−0.9813	0.6561	1.4269	0.7972
	5+ persons	0.0293	0.5483	1.3403	0.8222	−1.3111	0.9911
Vaccination (ref.: Not vaccinated)	At least one dose	8.8332***	0.4115	2.3453***	0.5682	6.4879***	0.7038
	No answer	0.1983	0.9652	−3.1264**	1.1968	3.3247*	1.5423
Region of residence (ref.: Montreal)	Quebec City	0.2715	0.3305	−0.0824	0.5062	0.3539	0.6063
	Other regions	0.8166***	0.2062	0.1127	0.3261	0.7039	0.3869
Sector/Occupation (ref.: Finance & Prof. Services)	Agriculture & Construction	0.4979	0.5169	3.0421***	0.8105	−2.5442**	0.9643
	Public Administration	1.5975***	0.4043	0.1865	0.6037	1.4110	0.7288
	Retail & Services	0.7815	0.4133	−0.3220	0.6194	1.1034	0.7469
	Manufacturing & Transportation	−0.3337	0.4117	−0.1232	0.6276	−0.2104	0.7529
	Education	7.2921***	0.5298	2.5232**	0.8105	4.7688***	0.9713
	Healthcare	3.2755***	0.4574	2.9821***	0.7034	0.2935	0.8417
	Retired	−1.5389***	0.4066	−0.9961	0.6814	−0.5428	0.7956
	Student	1.4927**	0.5149	−0.8354	0.6789	2.3282**	0.8549
	At home/Unemployed	−1.0506*	0.4652	−1.1576	0.6857	0.1069	0.8311
Constant	Constant	8.1364***	0.8096	-	-	-	-
	Week fixed effects	Incl.		Incl.		Incl.	
Mean of dep var. (%)		13.501		13.074			
N		41,370		48,114			

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: **Associations between different risk measures and sociodemographic caracteristics**: The objective risk used in model (2) is derived from symptoms. Results can be interpreted as percentage point differences between the result and its reference group.

4.2 Are Relative Misperceptions Constant Over Time?

In the previous section, we neglected the time dimension and pooled all the waves of data collection together. An interesting question to ask is whether differences between subjective and objective risk assessments are constant over time for a given subgroup. To do this, we regress the risk measures on the same vector of sociodemographic characteristics following the methodology described in section 3, only this time by month of data collection. Hence, we get estimates of $RAB_{j,t}$ which are time dependent. Our data collection spans January to May, so we compute each regression 5 times. We then test the hypothesis that each coefficient is constant through time for a given risk measure using Wald tests. We summarize the results in Table 3 with an X indicating statistical significance at the 5% level (and therefore that there are time differences).

Overall, we first find relative stability of subjective risk perceptions. Only those with low household income (less than \$20,000), with 5 kids or more and working in the education sector exhibit variation over time (relative to the reference group). For the objective risk, there is substantial variation over time across occupational sectors, suggesting that actual risks did vary over time across sectors (relative to the reference group). A striking result, however, is that there is strong stability of relative misperceptions (differences between subjective and objective) over the various months of data collection. Hence, there appears to be very little convergence in biases across groups.

Variable		Estimates: Subjective Risk	Objective Risk	RAB
Sex (ref.: Man)	Woman			
Age (ref.: 18-29)	30-39			
	40-49			
	50-59			
	60-69			
	70+			
HH income (ref.: 60-<80k)	<20k	X		
	20-<40k			
	40-<60k			
	80-<100k			
	≥100k			
Education (ref.: CEGEP)	Elementary			
	Secondary			
	University		X	
HH composition (ref.: 1 person)	With kid(s)			
	2 persons			
	3 persons			
	4 persons			
	5+ persons	X		
Vaccination (ref.: Not vaccinated)	At least one dose			
	No answer			
Region of residence (ref.: Montreal)	Quebec City			
	Other regions			
Sector/Occupation (ref.: Finance & Prof. Services)	Agriculture & Construction			
	Public Administration			
	Retail & Services		X	
	Manufacturing & Transportation		X	
	Education	X		
	Healthcare			
	Retired			
	Student		X	
	At home/Unemployed		X	

Table 3: **Consistency of the coefficients over time**: We estimate coefficients by month of data collection and test their time-invariance with Wald tests. We identify tests that suggest significant variation in time with an *X* in the table. Significance is determined at the 5% level.

4.3 Robustness

We decided to rely on symptom assessments to derive our objective risk measure. This hypothesis can be tested by comparing the marginal effects of two probit models, one that uses the objective risk derived from diagnosis and another that uses the one derived from symptoms. In Table 4, we present the results side-by-side. Both columns of marginal effects are mostly similar in terms of significance. Amplitudes vary, which is to be expected considering the differing means of the dependent variables.

Certain pairs of marginal effects stand out as having different signs between columns. Women are associated with a 1.5 pp increase in the probability of reporting symptoms despite being 0.4 pp less likely to have a positive (self-)diagnosis. A similar relation is found for vaccinated individuals, who are 2.3 pp more likely to report symptoms despite being 0.9 pp less likely to (self-)diagnose.

Vaccination did not prevent infection by the Omicron variant[10], but it did reduce symptoms. This could explain the difference captured by vaccination status, seeing as it is probably easier to self-diagnose when symptoms are harsher.

The cross-sectional positive association between education workers and objective risk vanishes when considering diagnosis rather than symptoms. This could reflect the presence of viruses with similar symptoms to COVID-19 in schools, or a tendency to self-diagnose less among this group.

An alternative explanation is that certain demographic groups (older people, healthcare workers, certain regions) had easier access to rapid tests than others during their distribution in early 2022. This means that we could observe higher

[10] The INSPQ reports that vaccination does not prevent Omicron infection as much as it did previous variants `https://www.quebec.ca/nouvelles/actualites/details/le-variant-omicron-est-desormais-dominant-au-quebec-37199`

Variable		(1) Diagnosis Marginal Effects	(1) Diagnosis Std. Error	(2) Symptoms Marginal Effects	(2) Symptoms Std. Error
Sex (ref.: Man)	Woman	-0.3855^{*}	0.1859	1.4824^{***}	0.3136
Age (ref.: 18-29)	30-39	-1.4168^{***}	0.3893	-3.8806^{***}	0.6734
	40-49	-2.3253^{***}	0.3779	-8.2566^{***}	0.6430
	50-59	-2.8469^{***}	0.3856	-9.5089^{***}	0.6552
	60-69	-3.5181^{***}	0.4381	-12.5316^{***}	0.7381
	70+	-3.7254^{***}	0.4953	-14.2809^{***}	0.7962
HH income (ref.: 60 - <80k)	<20k	0.2001	0.4891	-0.5890	0.7800
	20 - <40k	-0.1917	0.3549	-1.2173^{*}	0.5834
	40 - <60k	-0.4005	0.3212	-0.7278	0.5375
	80 - <100k	-0.7370^{*}	0.3251	-1.1522^{*}	0.5551
	$\geq$100k	-0.8317^{**}	0.2922	-2.2574^{***}	0.4912
Education (ref.: CEGEP)	Elementary	0.9492	1.0261	1.6526	1.7115
	Secondary	0.3492	0.2165	-1.0429^{**}	0.3600
	University	0.6710^{**}	0.2325	1.5812^{***}	0.3941
HH composition (ref.: 1 person)	With kid(s)	1.9318^{***}	0.3536	4.4249^{***}	0.5678
	2 persons	0.1763	0.2620	0.1057	0.4373
	3 persons	0.1124	0.3614	1.1415	0.6196
	4 persons	-0.4491	0.3797	-0.9813	0.6561
	5+ persons	1.0733^{*}	0.5099	1.3403	0.8222
Vaccination (ref.: Not vaccinated)	At least one dose	-0.8570^{*}	0.3926	2.3453^{***}	0.5682
	No answer	-1.6646^{*}	0.8024	-3.1264^{**}	1.1968
Region of residence (ref.: Montreal)	Quebec City	0.0804	0.3027	-0.0824	0.5062
	Other regions	0.0910	0.1934	0.1127	0.3261
Sector/Occupation (ref.: Finance & Prof. Services)	Agriculture & Construction	1.1357^{**}	0.4867	3.0421^{***}	0.8105
	Public Administration	0.1449	0.3666	0.1865	0.6037
	Retail& Service	0.1050	0.3779	-0.3220	0.6194
	Manufacturing & Transportation	0.3458	0.3833	-0.1232	0.6276
	Education	-0.2415	0.4519	2.5232^{**}	0.8105
	Healthcare	0.6173	0.4216	2.9821^{***}	0.7034
	Retired	-0.4750	0.4084	-0.9961	0.6814
	Student	-0.1285	0.4069	-0.8354	0.6789
	At home/Unemployed	-1.2887^{***}	0.3660	-1.1576	0.6857
Mean of dep var. (%)		4.056		13.074	
N		48,114		48,114	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: **Comparison of the two objective risk measures**: Model (1) shows the marginal effects for the objective risk derived from (self-)diagnosis while model (2) uses the objective risk derived from symptoms (the measure used in the main analysis).

rates of diagnosis associated with certain groups not because of a higher relative risk of infection, but because of greater relative means of getting tested.

5 Discussion

In situations of uncertainty, individuals tend to base their actions not on the actual risk but on their perception of that risk. It is therefore important to study risk perception as part of the decision-making process. Policy geared towards prevention and awareness require information on risk misperception, in particular when it differs across segments of the population.

While most public health interventions would probably aim at reducing optimism regarding infection risk (i.e., increasing the perceived risk for those who underestimate the objective risk), a normative assessment would consider both optimism and pessimism as costly from a welfare perspective. In the context of externalities, optimism regarding risk (underestimation) is of course of great importance as a focus of intervention, since misperceptions impose a social cost on others. Correcting misperceptions among segments of the population who underestimate the risk becomes a way to mitigate propagation. It is also important to consider those who are pessimistic (overestimate), as they may take actions that reduce their current well-being relative to what they could achieve would they correctly perceive the risk. For example, avoiding all social contacts because one grossly overestimates the risk of infection can have adverse mental health consequences. It should therefore also be the focus of public health policy to help those segments of the population to correctly assess the risk, in this case by lowering risk perception. The bottom line is that both overprotection and underprotection can be damaging and should be considered from a welfare standpoint.

We uncover three novel findings. First, we find that subjective risk assessments are surprisingly in line with objective risks. Second, we find substantial variation in misperceptions within the population. Certain groups are particularly prone to such biases. We uncover that older, vaccinated individuals as well as those working in healthcare and education tend to overestimate their infection risk. Younger individuals and those with children are more likely to underestimate their infection risk. Third, we find that these differences in misperceptions are remarkably persistent over time. There appears to be little convergence in these differences across groups. These findings provide some information regarding the groups most likely to benefit from additional information about risks in a future pandemic. This exercise also demonstrates the added value of fielding repeated surveys to the general population during a pandemic, to learn not only about official prevalence of infections but also about risk assessments and other behaviors. The questionnaire used for this survey was short and therefore prohibited asking in detail about self-protection activities, for example. We think that public health authorities should plan for such data collection efforts to be rapidly put in place were there to be another pandemic of the sort we experienced from 2020 to 2022.

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