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An Evaluation of the Effect of the COVID-19 Pandemic on the Risk Tolerance of Financial Decision Makers

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ABSTRACT

This paper documents the negative effect of the COVID-19 pandemic on financial risk attitudes across a broad sample of financial decision makers (N = 18,913). Findings show that the risk tolerance of financial decision makers can be altered when an extreme economic, social, or environmental shock occurs. A general shift away from be willing to take financial risk was noted after the COVID-19 pandemic emergency declaration. The COVID-19 pandemic shifted risk preference downward for the majority of financial decision makers in this study.

1. Introduction

The worldwide COVID-19 pandemic that began in early 2020 prompted wide ranging policy, economic, and financial market reactions. Consider the impact COVID-19 emergency declarations had on G7 financial markets. Each G7 country (i.e., Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States) implemented wide ranging stay-at-home orders, social distancing recommendations, and business closure policies. These actions resulted in a decline in worldwide economic productivity and price declines in the securities markets (Akhtaruzzaman et al., 2020a).

The literature is replete with examples and descriptions of how the media covered the pandemic, the way macroeconomic policy was changed in response to the pandemic, and the way the securities markets reacted to economic events as fear of the pandemic spread (e.g., Akhtaruzzaman et al., 2020b, 2020c; Ashraf, 2020; Haroon & Rizvi, 2020; Lavelle, 2020). Less attention has been focused on describing how individual financial decision makers reacted to the pandemic. Much of what has been reported about individual and household reactions has shown that financial decision makers, prompted by nearly 24-hour media reports, were emotionally stressed as they dealt with conflicting emotions, such as fear, regret, and disappointment. While these types of emotions are generally assumed to be incorporated into and exhibited by a decision maker's willingness to engage in an investment or financial behavior that entails incurring uncertain potential gains and losses (Rabbani et al., 2017), the degree to which the COVID-19 pandemic altered the willingness of individual financial decision makers to take financial risk has not been thoroughly examined in the literature.

Examining changes in household-level financial risk tolerance (FRT) has important implications for those who make financial

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decisions. Evidence exists to show that extreme events can cause systemic adjustments to risk and return expectations (Merkle & Weber, 2014). For example, Farhi and Gabaix (2016) documented how rare but extreme events, such as an environmental disaster, can cause downward pressure on the financial markets. This downward force can shift macro-level supply and demand, as well as alter decision-maker risk perceptions (Kaplanski & Levy, 2010). Whether changes in market perceptions are associated with the willingness of financial decision makers to take risk has not been widely examined in the literature.

This paper adds to the existing literature on the role extreme macro-economic, social, and health events have in describing the FRT of decision makers by documenting the impact of the COVID-19 pandemic on the financial risk attitudes of a broad sample of financial decision makers. The purpose of the paper is twofold. The first purpose is to document how financial decision makers can be clustered together based on risk attitudes, demographic characteristics, and behavioral commonalities using a latent profile analytical technique. The second purpose is to document the association between FRT and the COVID-19 pandemic.

Findings from this study offer insights into the FRT of financial decision makers. Results from this study show that financial decision makers can be clustered into distinct groups, but that the demographic and behavioral factors comprising such clusters are inconsistent in describing FRT across periods. Findings also indicate that the COVID-19 pandemic shifted the FRT of financial decision makers from a general willingness to take risk towards greater risk aversion. A key takeaway from this study is that an extreme social, economic, or environmental shock likely increases risk aversion.

The remainder of this paper is structured as follows. The data and analytic approach is presented, followed by a presentation of the findings. The findings focus on describing financial decision makers by FRT clusters and documenting the extent to which FRT changed during the pandemic. The paper concludes with a summary of findings.

2. Data and Analysis

Data used in this study were obtained from a cross-sectional internet survey hosted by the Department of Financial Planning at the University of Missouri. The sample (N = 18,193) was intended to represent a wide segment of financial decision-makers interested in household financial topics, investing, and financial decision making. The sample was not designed to be nationally representative of the U.S. population. Data were collected over the period of late April 2019 through early July 2020. This period represented a 14-month cycle in which no COVID-19 cases were known to a point when cases of COVID-19 were in the millions. As such, the sampling time frame provides real-time insights in which to compare pre- and post-pandemic FRT.

The primary outcome variable of interest was FRT, measured using a 13-item scale developed by Grable and Lytton (1999). This propensity scale has been shown to be empirically reliable and valid (Grable et al., 2019; Kuzniak et al., 2015). In this study, FRT scores ranged from 13 to 47, with a mean and standard deviation of 28.27 and 4.94, respectively. The Cronbach's alpha for the scale was .71.

Data on the following additional variables were also collected in the survey. Education level was measured on the following ordinal scale: 1 = Some high school or less; 2 = High school graduate; 3 = Some college/trade/vocational training; 4 = Associate degree; 5 = Bachelor's degree; 6 = Graduate or professional degree. Age was measured with the following seven categories: 1 = Under 25; 2 = 25 to 34; 3 = 35 to 44; 4 = 45 to 54; 5 = 55 to 64; 6 = 65 to 74; and 7 = 75 and over. Marital status was coded dichotomously as 1 = single, otherwise 0 (i.e., married or living with a significant other). The proportion of equity assets held in each respondent's portfolio was assessed by asking what percentage of total assets, comprised of equities, cash, bonds, and other assets, was currently held in equities. Approximately 31% of assets, across the sample, were held in equities. Household income was measured as an ordinal variable with 1 = Less than $25,000; 2 = $25,000 to $49,999; 3 = $50,000 to $74,999; 4 = $75,000 to $99,999; and 5 = $100,000 or greater. Gender was coded as a binary variable, with 1 = male and 2 = female. Objective financial knowledge was measured with three questions measured dichotomously as correct or incorrect (Lusardi & Mitchell, 2011). Subjective financial knowledge was measured with the following item: "On a scale from one to five, how would you rate your overall financial knowledge of various financial topics?" Answers were coded on a scale ranging from 1 = not at all knowledgeable to 5 = extremely knowledgeable.

A multi-step latent profile analysis (LPA) technique was used to identify unobserved groups within the sample. First, respondents were split into pre- and post-pandemic samples. The pre-pandemic sample included those who completed the survey between April 29, 2019 (i.e., the beginning point of the survey) and January 21, 2020 (N = 10,592), whereas the post-pandemic sample included those who completed the survey between January 22, 2020 and July 1, 2020 (N = 7,601). The LPA model used all of the variables described above to form clusters of respondents in the pre-pandemic sample. The goal of the LPA was to cluster respondents into groups based on the latent attributes of those in the groups. The optimal number of clusters was identified using customary clustering benchmarks (Hair et al., 2018; Spurk et al., 2020). A standardized comparison of clusters using z-scores was used to identify similarities and differences between clusters. As described below, two clusters were identified as optimal. The LPA model was then re-estimated using data from the post-pandemic sample. Data from the pre- and post-pandemic periods was then compared. The comparison was made to determine the extent to which the pandemic explained the willingness of financial decision makers to take financial risk. It was

Table 1
LPA Model Selection Comparison

	NEC	AIC	BIC	Log-likelihood
Two clusters	.525506	209276.90	209457.00	-104612.40
Three clusters	.742621	209103.50	209422.20	-104505.80
Four clusters	.731309	209112.90	209577.10	-104489.50
Five clusters	.758250	211410.70	211625.70	-105674.30

hypothesized that the emergency pandemic declaration that occurred in late January 2020 acted as a negative external stimulus (i.e., quasi-treatment effect) that may have altered the subsequent risk tolerance of financial decision makers.

3. Results

Table 1 shows the results from the LPA model fitting stage of the study. Based on the pre-pandemic sample, two clusters were identified as optimal (i.e., Clusters A and B). The selection of two clusters was based on the similarity of the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC) across the models, in conjunction with the observation that the Normalized Entropy Criterion (NEC) was smallest for the two cluster solution (Hair et al., 2018; Lanza & Rhoades, 2013; Nest et al., 2020; Sarstedt, 2008).

Respondents in the post-pandemic sample were then grouped into clusters (i.e., Cluster C and D) using the same LPA methodology. The two-cluster solution from both the pre- and post-pandemic periods exhibited bell-shaped FRT distributions (see Figure 1). The normal distributions for each FRT subgroup, across the time periods, confirmed that respondents' willingness to take financial risk was not biased by sampling issues. These modelling results provide evidence that the shift in FRT between the pre- and post-pandemic

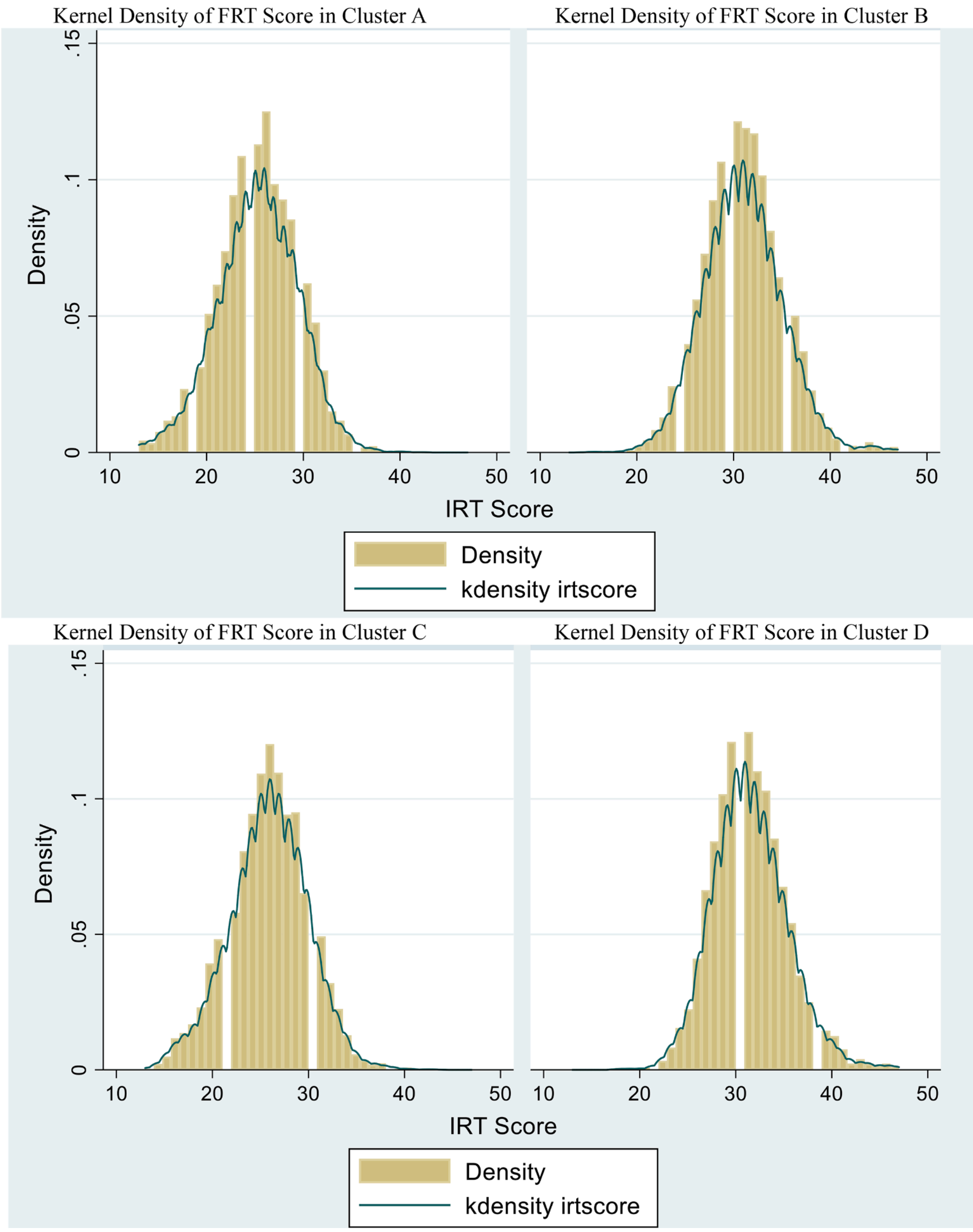

Figure 1. Histogram and Kernel Density of Financial Risk Tolerance Scores by Clusters

periods found in this study, as discussed below, corresponded, in large part, to events associated with the emergency pandemic declaration.

Although several differences between clusters A and B and clusters C and D were noted, the primary difference between clusters was that clusters A and C were comprised of those with a lower tolerance for financial risk, whereas those in the clusters B and D exhibited a higher risk tolerance. Table 2 shows the descriptive statistics associated with each cluster across the two time periods. Given the way that the clusters were developed, it was not surprising that the profile of those in Cluster A (i.e., the pre-pandemic low risk-tolerance group) was similar to the profile of those in Cluster C (i.e., the post-pandemic low risk-tolerance group), or that the profile of those in Cluster B (i.e., the pre-pandemic high risk-tolerance group) was similar to that of those in Cluster D (i.e., the post-pandemic high risk-tolerance group). Essentially, the demographic and behavioral factors comprising each cluster were relatively stable with little variability noted across the clusters.

Table 3 provides a description of the characteristics of those in each cluster. The second and third columns show data for the pre-pandemic period, whereas the last two columns show data for the post-pandemic period. It was determined that FRT scores increased from the pre-pandemic period to the post-pandemic period (i.e., from Cluster A to Cluster C and Cluster B to Cluster D). Prior to the pandemic, the average FRT score for those in Cluster A was 25.46. The average pre-pandemic FRT score for those in Cluster B was 30.78. Post-pandemic, FRT scores increased to 26.11 for those in Cluster C and 31.19 for those in Cluster D.

Respondents who exhibited higher FRT scores (i.e., those in Clusters B and D) were found to (a) have higher subjective knowledge,

Table 2
Descriptive Profile of Study Participants: Mean (SD) or Frequency (%)

	Total (n = 18,494)	Pre-pandemic Clusters (n = 10,592)		Post-pandemic Clusters (n = 7,601)	
		Cluster A (n = 5,209)	Cluster B (n = 5,383)	Cluster C (n = 4,164)	Cluster D (n = 3,437)
Grouping criteria					
FRT score	28.27 (4.94)	25.31 (4.13)	31.00 (4.07)	25.85 (4.08)	31.50 (3.89)
Comparison variable					
Obj. Fin Know	1.70 (.56)	1.57 (.63)	1.85 (.41)	1.57 (.63)	1.85 (.39)
Sub. Fin Know	3.29 (1.02)	2.74 90)	3.88 (.82)	2.73 (.89)	3.89 (.77)
Single (Y=1/N=0)	11,681 (63.16%)	3,139 (60.76%)	3,538 (66.37%)	2,504 (60.63%)	2,102 (61.68%)
Female (Y=1/N=0)	7,385 (39.93%)	3,392 (65.66%)	880 (16.51%)	2,503 (60.61%)	522 (15.32%)
Age					
25-34	8,790 (48.47%)	2,534 (49.05%)	2,417 (45.34%)	2,171 (52.57%)	1,639 (48.09%)
35-44	4,566 (25.18%)	1,186 (22.96%)	1,442 (27.05%)	1,030 (24.94%)	890 (26.12%)
45-54	2,442 (13.47%)	647 (12.52%)	803 (15.06%)	440 (10.65%)	531 (15.58%)
55-64	1,457 (8.02%)	441 (8.54%)	448 (8.40%)	290 (7.02%)	258 (7.57%)
65-74	607 (3.35%)	280 (5.42%)	119 (2.23%)	164 (3.97%)	35 (1.03%)
Over 75	272 (1.50%)	78 (1.51%)	102 (1.91%)	35 (.85%)	55 (1.61%)
Education					
Lower than high	345 (1.90%)	98 (1.90%)	112 (2.10%)	78 (1.89%)	45 (1.32%)
High school	855 (4.71%)	236 (4.57%)	232 (4.35%)	261 (6.32%)	109 (3.20%)
Some college	2,865 (15.79%)	1,164 (22.53%)	507 (9.51%)	799 (19.35%)	380 (11.15%)
Associate	2,193 (12.08%)	891 (17.25%)	344 (6.45%)	685 (16.59%)	262 (7.69%)
Bachelor's	5,991 (33.01%)	1,632 (31.59%)	1,831 (34.35%)	1,264 (30.61%)	1,238 (36.33%)
Graduate	5,900 (32.51%)	1,145 (22.16%)	2,305 (43.24%)	1,043 (25.25%)	1,374 (40.32%)
Income					
Lower than $25k	2,137 (11.82%)	810 (15.68%)	448 (8.40%)	618 (14.96%)	253 (7.42%)
$25k - $49.9k	3,530 (19.52%)	1,261 (24.41%)	755 (14.16%)	1,018 (24.65%)	488 (14.32%)
$50k - $74.9k	3,480 (19.25%)	1,185 (22.94%)	856 (16.06%)	900 (21.79%)	530 (15.55%)
$75k - $99.9k	2,831 (15.66%)	789 (15.27%)	837 (15.70%)	695 (16.83%)	503 (14.76%)
Over $100k	6,104 (33.76%)	1,121 (21.70%)	2,435 (45.68%)	899 (21.77%)	1,634 (47.95%)
Equity ratio	30.83 (32.79)	20.58 (28.80)	43.05 (33.42)	20.56 (28.22)	43.01 (32.65)

Table 3
LPA Clustering Results Pre- and Post-Pandemic

	Pre-pandemic Clusters (n = 10,592)		Post-pandemic Clusters (n = 7,601)	
	Cluster A (n = 5,209)	Cluster B (n = 5,383)	Cluster C (n = 4,164)	Cluster D (n = 3,437)
Grouping criteria				
FRT score	25.46***	30.78***	26.11***	31.19***
COVID case #	-	-	16495.97***	16686.33***
Comparison variable (ref. Cluster A)				
Objective financial knowledge	ref.	-.03	ref.	.05
Subjective financial knowledge	ref.	.94***	ref.	1.07***
Single (Y=1/N=0)	ref.	-1.70***	ref.	-1.67***
Female (Y=1/N=0)	ref.	-.33*	ref.	-.68***
Age (ref. 25-34)				
35-44	ref.	-.17	ref.	-.21
45-54	ref.	-1.03***	ref.	-.28
55-64	ref.	-1.75***	ref.	-1.22***
65-74	ref.	-2.82***	ref.	-2.60***
Over 75	ref.	-.71	ref.	-.53
Education (ref. high or lower)				
High school graduate	ref.	-1.82***	ref.	-.60
Some college	ref.	-2.70***	ref.	-.61
Associate degree	ref.	-2.62***	ref.	-.87
Bachelor's degree	ref.	-2.13***	ref.	-.36
Graduate or higher	ref.	-1.60***	ref.	-.34
Income (ref. lower than $25k)				
$25k - $49.9k	ref.	.33	ref.	.07
$50k - $74.9k	ref.	-.11	ref.	.08
$75k - $99.9k	ref.	.39	ref.	.34
Over $100k	ref.	.41	ref.	.64*
Equity ratio in wealth	ref.	.04***	ref.	.04***
Class Margin	.49	.51	.55	.45
Standard Error	.01	.01	.02	.02

Note. * $p < .05$; ** $p < .01$; *** $p < .001$. Cluster A in each period are reference group.

(b) be more likely to be married or living with a significant other, and (c) be more likely to be male. Compared to those with lower FRT scores (i.e., Clusters A and C), those with higher FRT scores were less likely to be between the ages of 55 to 74. The education effect disappeared during the post-pandemic period. Compared to those with a lower FRT score, respondents with higher FRT scores were found to have significantly lower attained education levels during the pre-pandemic period.

The row in Table 3 titled 'class margin' tells an interesting story. The percent indicates the proportion of respondents in each cluster. In the pre-pandemic period, the sample ratio between Clusters A and B was 49% to 51%; that is, 49% of the sample fell into the lower FRT cluster. In the post-pandemic period, the ratio of respondents in Clusters C and D changed to 55% to 45%. This suggests that post-pandemic, financial decision makers shifted from being more risk tolerant to more risk averse, even though the average FRT score increased from the pre- to post-pandemic period. It is worth noting that this shift occurred across categories of financial knowledge (i.e., subjective financial knowledge was higher in Clusters B and D in both periods). This suggests that those who were subjectively confident about their financial knowledge were more likely to exhibit higher FRT in the post-pandemic period. However, those who were not as confident about their financial knowledge changed from a willingness to take risk to a position of risk aversion.

4. Conclusion

This study adds to the literature in three ways. First, the study's findings suggest that, in general, two clusters likely exist among financial decision makers who are asked to reveal their willingness to take financial risk. The first cluster includes those with a low level of risk tolerance. Those in this cluster are more likely to report a lower level of financial knowledge. They are also more likely to be female, have lower household income, and own fewer equity investments. The second cluster includes those with a greater willingness to take financial risk. Those fitting this profile tend to be married men with more financial knowledge. These profiles match what is typically reported in the literature.

Second, the role of demographic and behavioral factors in describing FRT, especially during periods of social and economic crisis, appear to be inconsistent. Consider the findings related to the education and subjective financial knowledge measures used in this study. While it may seem reasonable to use attained educational status as an indicator for financial knowledge, the results from this study indicate that applying this assumption in practice may result in problematic outcomes. As described in this study, education was a significant factor describing the clusters during the pre-pandemic period; however, differences by education were not significant in the post-pandemic period. On the other hand, subjective financial knowledge was found to be significantly higher pre- and post-pandemic for those in the high risk-tolerance clusters (i.e., Clusters B and D). This indicates that research that attempts to estimate an association between an extreme economic, social, or environmental event and FRT should focus on the descriptive power of behavioral factors (e.g., subjective financial knowledge) more so than demographic factors (e.g., education, age, income).

Third, an extreme economic, social, and environmental stressor, such as the onset of a health pandemic, can be seen as analogous to a quasi-experimental treatment factor when a risk-tolerance measure is the outcome variable. As shown in the bottom row of Table 3, pre-pandemic, 49% of the sample was classified as having a low tolerance for risk. However, post-pandemic, the ratio changed significantly. A general shift away from being willing to take more financial risk was noted after the emergency declaration (i.e., 55% of the sample was grouped in Cluster C). This means that negative external events are not only associated with market volatility, such events can also describe shifts in the willingness of financial decision makers to take risk. The COVID-19 pandemic shifted risk tolerance downward for the majority of financial decision makers, while simultaneously moving the average FRT score across the sample higher. As such, it is reasonable to conclude that an extreme economic, social, or environmental shock, while on the average negative, does not affect all financial decision makers the same way.

CRediT authorship contribution statement

Wookjae Heo: Conceptualization, Methodology, Writing - original draft. **Abed Rabbani:** Investigation, Resources, Data curation, Visualization, Writing - review & editing. **John E. Grable:** Project administration, Validation, Writing - review & editing.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2020.101842.

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