Strategic Sophistication and Collective Action: Theory and Evidence

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First version: June 30, 2022 This version: March 2, 2024

Abstract

This study investigates the effects of individuals' strategic sophistication, measured by level-k type, on collective action in the context of social distancing during the early stages of the COVID-19 pandemic. We build a weakest-link public goods game with the private cost of social distancing, in which agents are heterogeneous in level-k types. We find that players with higher level-k types are more likely to engage in social-distancing behaviors. We test this hypothesis using large-scale nationally representative survey data that measure level-k types through incentivized experiments. Our empirical findings provide consistent evidence for the theoretical prediction, highlighting the importance of understanding the role of level-k theory in real-world collective action problems.

JEL Classification: C72, D91, H12, I12

Keywords: collective action problem; COVID-19; level-k theory; social-distancing behavior; strategic sophistication

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1 Introduction

Standard equilibrium analyses of game theory assume that agents have equally unlimited strategic sophistication. However, empirical evidence shows that individuals are heterogeneous in terms of their strategic sophistication levels (e.g., Alaoui and Penta 2016; Crawford et al. 2013; Rabin 2013). The "level-k" theory, also known as the cognitive hierarchy theory, provides a conceptual framework that reconciles the discrepancy between the canonical model's assumption of strategic sophistication and empirical evidence (e.g., Camerer et al. 2004a; Nagel 1995; Stahl and Wilson 1994). It describes the behavior of agents who best respond based on their beliefs about others' strategic sophistication levels.[1] The level-k theory has successfully explained a wide range of subjects' boundedly rational behaviors in lab experiments (e.g., Camerer et al. 2004a; Camerer et al. 2004b; Nagel 1995).

In addition to the empirical evidence obtained from controlled lab experiments, recent studies document real-world examples of how strategically more sophisticated individuals exhibit higher individual-level achievements in terms of education, economic outcomes, and professional asset trading (e.g., Angrisani et al. 2022; Choi et al. 2022; Fe et al. 2022). Given the strategic nature of level-k theory, it is crucial to understand how heterogeneous strategic sophistication levels affect individuals' behaviors in *collective action* settings because of social welfare implications. However, to the best of our knowledge, no attempts have been made to analyze the relationship between the theory of strategic sophistication and individuals' collective action choices in a real-world setting.

We fill this gap in the literature by examining how individuals' heterogeneous strategic sophistication affects collective action measured by social-distancing behavior during the COVID-19 pandemic.[2] Previous studies on the determinants of social distancing behavior

[1] In a standard level-k model, each agent is defined as a level-k player with $k \in \mathbb{N}_0$. A level-k agent is assumed to *best respond* to the belief that each of the other players is a level-$(k-1)$ player, assuming that level-0 agents randomly choose an action.

[2] In the absence of vaccines or pharmaceutical treatments, social-distancing measures are the key strategies to minimize the adverse health impact of COVID-19 (e.g., Fazio et al. 2021; Lammers et al. 2020). Farboodi et al. (2021) also develop a theoretical framework to analyze how individuals balance the benefits

(e.g., Brodeur et al. 2021; Campos-Mercade et al. 2021a; Fang et al. 2022; Muller and Rau 2021) have documented that the success of these measures critically depends on society-wide cooperation, because an individual's decision to comply with social-distancing measures could be affected by others. Unlike other diseases that are spread by physical contacts (e.g., AIDS), COVID-19 is airborne and thus the probability of infection depends on others' compliance with social-distancing measures. As such, social distancing behaviors can be strategically complementary: people are more likely to comply with costly social distancing measures when they believe that others are also practicing them.

To capture this strategic situation, we first present a social-distancing game in which agents with heterogeneous level-k types and the cost of social-distancing choice simultaneously decide whether to practice social-distancing behavior based on their beliefs about other players' behavior. The model describes a situation in which two agents were randomly chosen from the population to play the weakest-link public goods game (Hirshleifer 1983; Vicary 1990). As we are interested in modeling strategic social-distancing behaviors at the early stage of the pandemic when there was no strong social-distancing enforcement yet, we assume that level-0 agents are unlikely to take social-distancing decisions.[3] Under some conditions, we show that the likelihood of practicing costly social-distancing behavior strictly increases as the level-k (i.e., the strategic sophistication level) increases.[4]

We test the theoretical prediction using nationally representative panel survey data of older Singaporeans from the Singapore Life Panel (SLP), in which a measure of the level-k type is identified through an online lab experiment provided by Choi et al. (2022). By exploiting the longitudinal features of the data, we examine how an individual's probability of leaving home changed daily after the onset of the pandemic by level-k type, using a difference-

of socializing with the risks during pandemics. Their findings highlight the collective action problem caused by the inefficiency of social distancing behavior in a laissez-faire equilibrium. Our model simplifies this dynamic problem and captures its strategic nature. Kang et al. (2022) address similar efficiency concerns in a network context.

[3] In Section 2.3, both theoretical and empirical justifications are provided to support this assumption.

[4] This testable theoretical prediction also holds for the generalized cognitive hierarchy model (Chong et al. 2016) as provided in Appendix A.

in-differences (DID) model. Our DID estimates provide robust evidence that individuals with higher level-k types are less likely to leave home daily after the onset of the pandemic; that is, the probability of choosing social-distancing increases in the level-k type. Our results are robust to controlling for other effects such as IQ scores, educational attainment, cognitive empathy, and subjective risk preferences.

To examine the external validity of our baseline analysis, we use additional data from the Korean Labor and Income Panel Survey (KLIPS), which covers a nationally representative adult population in South Korea. We estimate the associations between individuals' level-k types and the probability of increasing outdoor activities, while controlling for demographic and socio-economic characteristics, subjective risk preferences, and other measures of cognitive abilities. We find consistent evidence that individuals with higher level-k types tend to exhibit social-distancing behaviors during the pandemic by reducing their outdoor activities.

This study contributes to the related literature in two ways. First, to the best of our knowledge, this study provides the first real-world evidence of the effects of strategic sophistication on collective actions as measured by social-distancing behaviors during the COVID-19 pandemic. Angrisani et al. (2022) show that professional traders' profits are determined by strategic sophistication rather than cognitive abilities or behavioral traits. Fe et al. (2022) provide evidence of how childhood cognitive skills are associated with strategic sophistication and adult outcomes. Choi et al. (2022) find that older individuals' strategic thinking skills are closely associated with labor market outcomes. Those previous studies have demonstrated the importance of strategic thinking skills for individual-level outcomes. Our study extends the literature by providing real-world evidence of the effects of strategic sophistication on collective actions with significant externality in the context of the COVID-19 pandemic.[5]

Second, this study adds to the literature on the determinants of preventive health behaviors. Under the commonly accepted presumption that "an ounce of prevention is worth a pound of cure," both policymakers and researchers focused on understanding how to en-

[5] Koriyama and Ozkes (2021) investigate the relationship between strategic sophistication levels and collective action in a controlled lab experiment setting.

courage individuals' preventive health behavior (e.g., Baicker et al. 2010; Hey and Patel 1983; Ward 2014). A growing number of studies have examined the relationship between non-pecuniary factors and preventive health behaviors (Madrian 2014). For example, existing studies demonstrate how individuals' risk preferences (Anderson and Mellor 2008), time preferences (Courtemanche et al. 2015; Harrison et al. 2010), prosociality (Campos-Mercade et al. 2021b), and misperception of their own health status (Arni et al. 2021) affect health-related behaviors and outcomes such as smoking, alcohol consumption, exercise and body mass index. In addition to these factors, an individual's cognitive ability is an important determinant of health-related behavior (Cawley and Ruhm 2011). Although the positive relationship between education and health has been widely documented, there is little evidence of the relationship between individuals' strategic sophistication levels and health-related behaviors. We complement the literature by providing evidence that strategic sophistication is an important determinant of individuals' preventive health behaviors.

The remainder of this paper is organized as follows. Section 2 presents a theory of level-k in social-distancing behavior. In Section 3 and Section 4, we provide the data and present the empirical results, respectively. Section 5 presents our conclusions. All proofs of the theoretical results, additional theoretical analyses, and robustness checks for the empirical analysis are presented in the appendices.

2 Theoretical Framework

2.1 Setup

A public goods game. We consider a variant of the weakest-link public goods game à la Hirshleifer (1983) with a voluntary provision of public goods, where agents are heterogeneous in both their contribution costs and strategic sophistication levels. There are two players, player 1 and player 2. Players choose simultaneously whether to contribute. Specifically, each player plays either C or NC, where C represents "contribute" to the public good provision and NC denotes "do not contribute." The cost of contribution is c^i to player i. The game's payoff matrix is shown in Table 1 as a function of players' actions and their contribution costs. A more general game payoff is considered in Appendix B, and the results hold under regular conditions.

Table 1: The payoff matrix of the public goods game

		player 2	
		NC	C
player 1	NC	$(0, 0)$	$(0, -c^2)$
	C	$(-c^1, 0)$	$(1 - c^1, 1 - c^2)$

We assume that each player's cost is random and privately known. It is drawn independently and identically from the cumulative distribution F over $[\underline{c}, \overline{c}] \subset \mathbb{R}$ with $\underline{c} < 0$ and $\overline{c} > 1$. F is continuous and increases strictly in $[\underline{c}, \overline{c}]$. We also require a unique c^* such that $F(c) = c$. All the above game environments are common knowledge among game players.

$F(0) > 0$ means that with a strictly positive probability, some agents have a negative contribution cost; that is, they are voluntarily willing to contribute to the public good, regardless of what the opponent player does. As such, it is the strictly dominant strategy to play C. By contrast, $F(1) < 1$ means that, with a strictly positive probability, some agents suffer from a high contribution cost that is strictly greater than 1. Thus, they never contribute to the public good; that is, playing NC is their strictly dominant strategy. Moreover, with a strictly positive probability, the costs of both players are $(0, 1)$. In this case, the game becomes a *coordination game*, and there are two pure-strategy Nash equilibria:(NC, NC) and (C, C). In other words, for player i, there is no strictly dominant strategy and her best-responding action depends on her belief about the other player's action, and vice versa. This is the point where the players' heterogeneous strategic sophistication types come into play in response to their opponents' actions.[6]

[6] As a benchmark case, if there is no heterogeneity in their strategic sophistication and the agents are fully rational, then there is a unique symmetric perfect Bayesian equilibrium, in which player i contributes to the public good if and only if $c^i \leq c^*$, where c^* is the unique cutoff cost with $F(c^*) = c^*$. In this benchmark case, the probability of contribution is $F(c^*)$, which is identical for all agents.

We introduce agents' heterogeneity in their strategic sophistication by adopting the standard level-k theory (Costa-Gomes et al. 2001; Costa-Gomes and Crawford 2006; Nagel 1995; Stahl and Wilson 1994).[7] We assume that the population is partitioned into types and that each player is described as a level-k player with $k \in \mathbb{N}_0$. Each level-0 player is assumed to be *non-strategic*, and the other level-k agents with $k \geq 1$ are assumed to *best respond* to the belief that the other player is a level-$(k-1)$ player.[8] In the next subsection, we analyze player 1's behavior as a function of her strategic sophistication type (i.e., level-k) regarding player 2's expected action and her own contribution cost (i.e., c^1) without loss of generality.

Discussions on the model. The previous two-person public goods game modeled strategic interactions within a large population, similar to other games with incomplete information. Two players were assumed to be randomly selected from the population, accounting for the uncertainty in social distancing costs and strategic sophistication. Treating each other as random draws avoids the need for an n-person game model. Hence, the proposed simple two-person game captures key economic insights without adding additional complexity.

The model aims to describe the early phase of the COVID-19 pandemic, when there were no government-imposed social-distancing rules (e.g., stay-at-home orders) yet. Thus, individuals were required to exhibit social-distancing behavior voluntarily by reducing their outdoor activities to prevent the spread of COVID-19. As a result, a collective action problem has emerged.

We describe individuals' social-distancing behaviors using the weakest-link public goods game (Hirshleifer 1983). Several elements of the COVID-19 pandemic illustrate how the weakest-link public goods game best describes an individual's incentive structure during the outbreak. First, COVID-19 has a relatively long incubation period and a high transmission rate (Lewis 2022). In addition, a significant number of the infected were asymptomatic;

[7] Our results remain the same for the cognitive hierarchy model (Camerer et al. 2004a) and its generalized version (Chong et al. 2016), with the same intuition as shown in Appendix A.

[8] Our results do not rely on this assumption. In Appendix A, we show that all the theoretical results hold for the cognitive hierarchy model in which a level-k player best responds to all lower levels under a perceived belief about the opponent's levels.

they were required to practice social-distancing behaviors and wear masks to protect others (Nogrady 2020). To minimize the risk of infection and protect vulnerable populations in the absence of vaccines, citizens are required to make sufficient social-distancing efforts (e.g., maintaining physical distance, avoiding large gatherings and crowded places, and limiting non-essential travel). Therefore, social-distancing behaviors during the early phase of the COVID-19 pandemic involved the weakest-link elements.

Our model address new strategic features of individual behavior during the pandemic. For example, as noted by Agranov et al. (2021), vaccine adoption suffers from another collective action problem, free-riding incentives, and individuals' adoption decisions are strategic substitutes. By contrast, the main theoretical hypothesis of the current paper comes from the feature of agents' actions as strategic complements.

We finally provide a series of technical remarks about the assumptions on the common cost distribution F. First, the continuity and strict monotonicity of F are frequently employed in collective action models with private costs (e.g., Palfrey and Rosenthal 1985). The continuity assumption, in particular, is essential; if F is not continuous but right-continuous, then for some agents' beliefs, the cutoff cost may not be well-defined. Second, the assumption of a unique fixed point is not necessary for our analysis. This assumption serves to simplify our main and comparative static analyses. Alternatively, one could assume a finite number of fixed points that satisfy the fixed point equation. Third, the common cost distribution assumption can be relaxed. One might be interested in scenarios where agents have heterogeneous cost distributions depending on their strategic sophistication levels. For example, strategic sophistication levels are positively related to higher education and labor market supply (Choi et al. 2022; Fe et al. 2022). Hence, one may assume that the cost distribution for lower sophistication levels first-order stochastically dominates that for higher sophistication levels. The main testable theoretical result, as shown in Proposition 2-(a), still holds under this extension by Proposition 3.

2.2 Analysis

We assume that a level-0 player plays C with probability $\pi_0 \in (0,1)$.[9] For example, π_0 can be chosen as $F(0)$ only if the level-0 agents with negative contribution costs choose C. Similarly, $\pi_0 = F(1)$ is also possible if (C, C) is a focal point of the agents with a provision cost of less than 1 during the COVID-19 pandemic; the agents whose social-distancing cost outweighs the value of public goods take action NC.[10]

Other level-k players' best-responding actions are characterized by their cutoff strategy, which is optimal with respect to their beliefs about the opponent's behavior. Let π_{k-1} be level-$(k-1)$ player's probability of playing C. Assuming that the other player is a level-$(k-1)$, it is the best response for a level-k player to play C if and only if the provision cost is less than or equal to π_{k-1}. Thus, $c_k = \pi_{k-1}$ is the cutoff cost at which the player becomes indifferent to the two actions. Moreover, from a level-$(k+1)$ player's perspective, a level-k player plays C with probability $F(c_{k-1})$. Hence, a level-$(k+1)$ player plays C if and only if $c \leq c_{k+1} = F(c_{k-1})$. Consequently, we can recursively define each level-k player's cutoff cost c_k and the resulting probability of choosing C, π_k and as follows:

Proposition 1 *Let $\pi_0 \in (0,1)$ be the probability that a level-0 player chooses action C. Then, for any $k \geq 1$, a level-k player plays a cutoff strategy with cutoff cost c_k, where c_k is recursively defined as $c_k = \pi_{k-1}$ with $\pi_{k-1} = \pi_0$ if $k = 1$ and $\pi_{k-1} = F(c_{k-1})$ if $k \geq 2$.*

2.3 Strategic Sophistication and Contribution Behavior

We now examine the properties of players' behaviors. We present (i) the monotonicity of the cutoff strategies in the level-k type and the resulting monotonicity of contribution

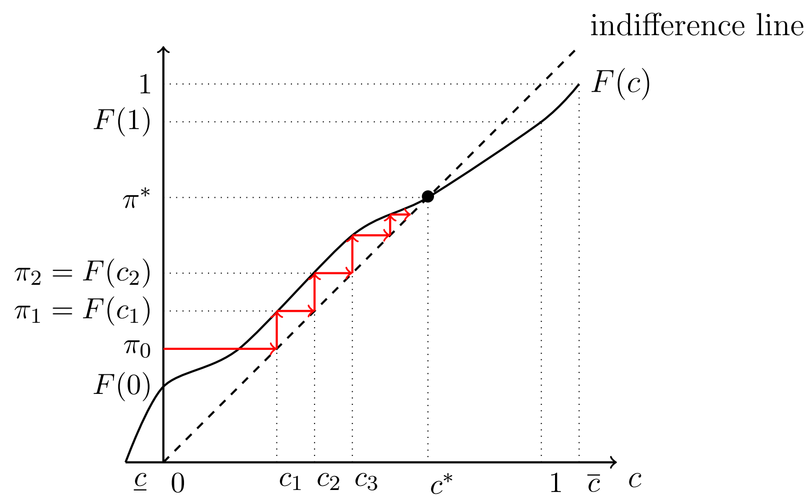
[9] In a standard level-k model, level-0 players are assumed to choose an action uniformly at random over the set of strategies (Arad and Rubinstein 2012; Chong et al. 2016). In our model, level-0 players can be assumed to play C with probability $\pi_0 = \frac{1}{2}$, regardless of their costs. Some studies (e.g., Chong et al. 2016) rule out the possibility of choosing a strictly dominated action and impose an additional structure. In the current model, any choice of $\pi_0 \in (F(0), F(1))$ incorporates the restriction. In both cases, π_0 can be greater or smaller than c^*, and each premise in Proposition 2 holds.

[10] For instance, an agent who needs regular renal dialysis cannot stop visiting a hospital during the pandemic. In our model, such an agent's social-distancing cost is assumed to be strictly greater than 1, the value of preventing the spread of the disease at the early stage of the pandemic.

probability, and (ii) monotone comparative static results in a change in the cost function.

Monotonicity of the contribution probability. We find that the probability of choosing action C is *positively* associated with agents' strategic sophistication levels if the level-0 player's likelihood of choosing action C is relatively low. Specifically, Figure 1 describes the situation in which π_0 is lower than $\pi^* = F(c^*)$. In the figure, the indifference line represents the pairs of (c, π) in which an agent with contribution cost c with belief π is indifferent between playing C and NC. Given this level-0 player's behavior, the level-1 player's cutoff cost c_1 is determined as $c_1 = \pi_0$. A level-2 player now believes that a level-1 player plays C with probability $\pi_1 = F(c_1)$. As such, the cutoff cost c_2 is determined by $c_2 = F(c_1)$. As $\pi_0 < \pi^*$, c_1 is strictly smaller than c^*, which further implies that $\pi_1 < \pi^*$ and $c_2 < c^*$. This implies that $c_1 < c_2$. In other words, when π_0 is relatively low, strategic sophistication generates a best-response dynamic in which a level-2 player's cutoff cost c_2 is strictly greater than a level-1 player's cutoff cost c_1.

Figure 1: Illustration of increasing cutoff costs at strategic sophistication levels



Importantly, by the induction principle, the same increasing property emerges for higher level-k types. Consequently, we obtain the property that the sequence of cutoff costs $\{c_k\}_{k\geq1}$ strictly increases as the strategic sophistication parameter k increases.

The opposite decreasing dynamic arises when π_0 is relatively high because $\pi_0 > \pi^* =$

$F(c^*)$. Note that from Proposition 1, for $k \geq 1$, a level-k player's cutoff cost c_k satisfies $c_k = F(\pi_{k-1})$, and each level-$(k+1)$ player believes that the opponent player plays C with probability $\pi_k = F(c_k)$. Thus, $c_{k+1} = F(c_k) < c_k$ because $F(c) < c$ for all $c > c^*$. Then, by the induction principle, the sequence of cutoff costs $\{c_k\}_{k\geq 1}$ strictly decreases in the strategic sophistication parameter k. Therefore, players are less likely to choose C as their strategic sophistication level increases.

If $\pi_0 = \pi^* = F(c^*)$, heterogeneous strategic sophistication does not play a role, as each level-k player has a self-fulfilling belief about the opponent: $c_k = F(c_{k-1}) = F(c^*) = \pi_0$ for all $k \geq 1$. Consequently, the sequence of cutoff costs $\{c_k\}_{k\geq 1}$ is constant in the level-k type, and the probability of choosing C is $\pi^* = F(c^*)$.

The following proposition summarizes the discussion above.

Proposition 2 *Let π_0 be given and π_k be a level-k player's probability of choosing action C for $k \geq 1$. Then,*

(a) if $\pi_0 < F(c^*)$, then π_k is strictly increasing in k;

(b) if $\pi_0 > F(c^*)$, then π_k is strictly decreasing in k; and

(c) if $\pi_0 = F(c^*)$, then π_k is constant in k.

Each result in the proposition above is a testable hypothesis as a function of π_0. In particular, in Section 3 and Section 4, we empirically test the increasing probability of choosing action C by using large-scale population-representative data. Although Proposition 2 provides two directions of monotonicity, (a) and (b), the increasing property (a) is a more reasonable hypothesis to test for several reasons. First, because our model considers the situation in which individuals choose social distancing behavior at an early stage of the pandemic without an enforced order (e.g., lockdown), people may be uncertain about others' behaviors. In this regard, theoretically, we can consider a situation in which level-1 players consider the range of possible choices of π_0 for level-0 players and choose an action that is robust to this uncertainty.[11] Formally, let $\mathcal{P} \subseteq [F(0), F(1)]$ be the set of beliefs about

[11] This theoretical argument is in line with that of Caballero and Simsek (2013). They examined banks'

level-0 players' behaviors excluding the strictly dominant strategies for sufficiently high- or low-cost players. Following the maximin expected utility representation (Gilboa and Schmeidler 1989), it is the best response for a level-1 player with provision cost c^1 to choose C if $\min_{\widetilde{\pi}_0 \in \mathcal{P}} \widetilde{\pi}_0(1 - c^1) + (1 - \widetilde{\pi}_0)(-c^1) \geq 0$, and the equality holds if and only if $\widetilde{\pi}_0 = F(0)$. Thus, the cutoff cost for level-1 players is $c_1 = F(0) < c^*$, which results in a best-response dynamic consistent with (a).[12]

Second, in the context of social-distancing behavior at the early stage of the COVID-19 pandemic, the natural *status-quo* action is NC; that is, "behave as people did before the pandemic." Hence, at an early stage of the spread of the virus, at least for non-strategic people, it is natural to expect them to behave as they did before the pandemic, and strategic level-1 players best respond to their behaviors. Indeed, we found that, in our data, the subjects identified as level-0 players did not exhibit statistically significant differences in outdoor activity levels. In addition, benefiting from the panel structure of the data, we test hypothesis (a) by including individual fixed effects and examine whether higher level-k types are more likely to change their behaviors in line with social-distancing behavior, when *compared with* their behaviors prior to the pandemic.

Notably, each result in Proposition 2-(a) does not predict the magnitude of the increase. In particular, the magnitude of $\triangle\pi_k = (\pi_k - \pi_{k-1}) > 0$ for $k \geq 1$ may fluctuate as k changes, depending on the shape of the cost function. As we do not impose any further restrictions on its shape, the proposition remains silent. We will return to this point in a later empirical test result (Proposition 2-(a)).

In the next section, we empirically demonstrate that people are more likely to exhibit social-distancing behavior as their strategic sophistication levels increase. Our empirical tests include variables related to other-regarding and risk preferences. The level of public goods provision is positively correlated with other-regarding preferences, such as altruism and trust.

strategies in financial *crises*, where banks are uncertain about the financial network of cross-exposures, and financial crises stem from the endogenous complexity of the network structure. Thus, in their model, each bank considers the possibility of multiple financial networks and chooses an action based on this uncertainty.

[12] The single crossing assumption of F with the 45° line is not necessary if we assume $\pi_0 = F(0)$.

Moreover, strategic agents' behaviors may be affected by their risk preferences. Hence, we include these variables to account for the potential impact of these preferences and the covariance among them, along with the level-k types.[13] Furthermore, we include other variables representing individual demographics such as income, educational level, and gender, because they are associated with strategic sophistication levels.[14] We also examine whether these variables affect social distancing behavior after the outbreak of the COVID-19 pandemic, using them as control variables and the variables interacting with a dummy variable indicating the pandemic period.

Monotonicity in cost distribution. We discuss how players' behaviors and the resulting best-response dynamic respond to a change in cost distribution. For simplicity, consider two cumulative distributions F and G, where G is under the first-order stochastic dominance of F: $G(c) > F(c)$ for all $c \in (\underline{c}, \overline{c})$. Thus, players' costs from G are more likely to be lower than those from F. As before, we assume that both F and G satisfy the assumption that there is a unique cost at which the graph of a function intersects the 45° line. Let c_F^* and c_G^* be the costs satisfying $F(c_F^*) = c_F^*$ and $G(c_G^*) = c_G^*$. Because G is under the first-order stochastic dominance of F, we have $c_F^* < c_G^*$. Figure 2 illustrates the relationship and properties of F and G.

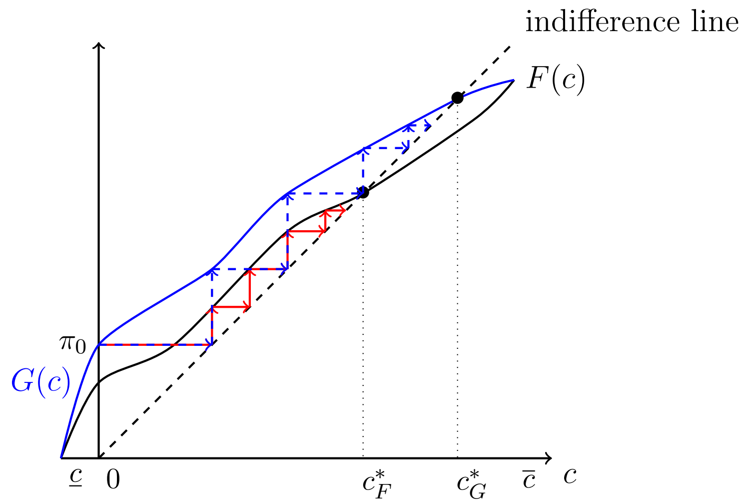
We find that level-k players are *more likely* to play action C for all $k \geq 0$ as the cost distribution decreases in the first-order stochastic dominance sense. Figure 2 illustrates this result. In this figure, a common value of π_0 was selected to ensure that $\pi_0 < G(c_G^*) < F(c_F^*)$.[15] Thus, under both distributions, strategic sophistication generates increasing best-response dynamics described by Proposition 2-(a). The red solid arrows denote the increasing

[13]During the COVID-19 pandemic, the adoption of social-distancing behavior could be influenced by economic preferences and factors such as other-regarding preferences, risk preferences, and demographic characteristics (e.g., Asri et al. 2021; Campos-Mercade et al. 2021a; Fang et al. 2022; Kim and Jung 2022; Muller and Rau 2021).

[14]For example, Choi et al. (2022) report that strategic sophistication levels are positively correlated with IQ scores and other-regarding preference measures. See Kagel and Roth (1995) and Kagel and Roth (2020) for the comprehensive surveys.

[15]This assumption is for illustration purposes and not necessarily for obtaining any of our results.

Figure 2: Illustration of impact of cost distribution shifting



dynamics under distribution F, which has a first-order stochastic dominance over distribution G. The blue dashed arrows illustrate the increasing dynamic under distribution G.

Under both distributions, the level-1 players' cutoff costs are identical because π_0 is the same. However, their probability of choosing action C is strictly higher under G, and level-1 players are more likely to incur lower costs under G. Given this feature, the level-2 players' cutoff cost is strictly greater under distribution G than that under F, and thus the probability of choosing C is strictly higher for G. The same logic applies to the other higher level-k types.

There are two effects on the amount of increase: (i) direct and (ii) indirect. For example, consider level-2 players' probability of choosing C. For the direct effect, there are more level-2 players whose costs are lower than that under F. For the indirect effect, because more level-1 players play action C, the cutoff cost for level-2 players increases; consequently, more level-2 players play action C. Interestingly, because of the recursive structure, the indirect effect is cumulative: for example, an increase in level-1 players' likelihood of playing C affects level-3 players' likelihood of playing C because level-2 players are more likely to play C.

If π_0 is strictly greater than $G(c^*_G)$, the best-response dynamics decrease under both distributions. However, because the graph of F is under G for any level-k type with $k \geq 1$, the probability of choosing C under G is strictly higher than under F. Therefore, players are more likely to play action C under the dominated distribution G. If $\pi_0 \in [F(c_F^*), G(c_G^*)]$, then the best-response dynamic under G increases in k but the dynamic under F decreases. Thus, the cutoff cost under G is strictly higher than that under F for all k. Again, the probability of choosing C under G is strictly higher than that under F for any level-k type with $k \geq 1$. Consequently, independent of the common choice of π_0, a first-order stochastic decrease in the cost distribution results in a higher probability of contribution for all level-k types with $k \geq 1$.

The following proposition summarizes this discussion.

Proposition 3 *Suppose that F first-order stochastically dominates G. Let π_0 be the probability of choosing C for level-0 players. Let $\pi_k(\theta)$ be the probability of level-k players' choosing action C under the distribution $\theta \in \{F, G\}$. Then, $\pi_k(G) \geq \pi_k(F)$ for all k and the strict inequality holds whenever $k \geq 1$.*

The above comparative static result provides an important policy implication. In the early stages of a viral outbreak, governments and other organizations can help reduce social-distancing costs by ensuring a steady supply of essential items such as food, water, and basic medical supplies (e.g., face masks). By ensuring that people have access to basic necessities, governments, and other organizations can help them comply with social distancing measures (e.g., HLPE Steering Committee 2021; Ranney et al. 2020; WHO and UNICEF 2020). This is a direct effect.

If people have different levels of strategic sophistication, then there is an indirect effect, especially when those with the lowest level of strategic sophistication are unlikely to follow the order of social-distancing behavior (i.e., π_0 is low). The provision of necessities leads to more effective social distancing for level-0 people, which in turn leads to more effective social distancing for level-1 people, and so on. This virtuous cycle helps to reduce the spread of the virus and ultimately leads to fewer people becoming sick or dying during the early stage of the pandemic.

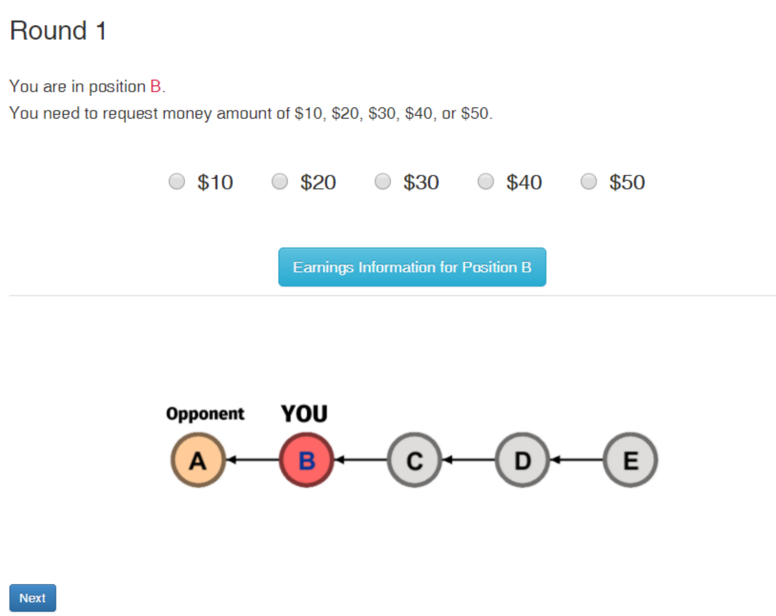
Finally, we note that all theoretical results thus far (i.e., Propositions 1–3) hold for a general payoff structure under regularity assumptions. See Appendix B for further details.

3 Experimental Design and Measurement

3.1 Measuring Level-*k* Types

In 2017, both the SLP and KLIPS, which are large-scale and nationally representative surveys in Singapore and South Korea, respectively, jointly conducted identical survey experiments to measure the degree of strategic sophistication.[16] We use strategic sophistication to measure an individual's ability to engage in introspective thinking. It was measured using a five-person simultaneous-move game (the Line Game), which is a variant of the 11-20 money-request game (Arad and Rubinstein 2012) and is similar to that of Kneeland (2015). Figure 3 illustrates a sample screenshot of the game.

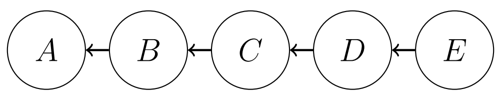
Figure 3: Screenshot of Line Game in position B (source: Choi et al. (2022))



[16]For this experiment, the KLIPS invited a small randomly chosen sample (slightly fewer than 800) of their baseline survey participants, and the SLP invited about 2,000 participants of their baseline survey participants aged 50–65 years. Choi et al. (2022) originally designed and implemented this experiment to estimate the role of strategic thinking skills in collective labor supply decisions. Much of the discussion on strategic sophistication as a measure of strategic thinking skills is borrowed from their study.

Players are assigned to each of the five positions (A, B, C, D, and E) in five rounds in a randomized order. Players choose money requests simultaneously and independently. A player in position A requests either S$10 (US$7.30) or S$50 (US$36.5) while players in any other position request for either of these five options: S$10, S$20, S$30, S$40, or S$50.[17] The payoff for a player in position A is the amount of money requested. The payoffs for the players in other positions consist of two parts: each player receives (i) the amount of money requested and (ii) an additional amount of S$100 if and only if the money requested is S$10, which is strictly lower than the money requested by an opponent. The opponent of each player is defined as the player who occupies a position to the left of the player in the line network, as illustrated in Figure 4.[18]

Figure 4: Illustration of the neighboring structure in the Line Game



In the game, assuming full rationality, we can identify a unique Nash equilibrium by applying an iterated deletion of strictly dominated strategies (Osborne 2003). First, S$10 is the strictly dominated action in position A; thus, a player in position A must play S$50. Second, given the action of the player in position A, it is a strictly dominated action for the player in position B to choose any action other than S$40. Third, with the deletion of strictly dominated actions of the player in position B, it is a strictly dominated action for the player in position C to choose any action other than S$30. This iterative process continues, resulting in choices of S$20 and S$10 by the players in positions D and E, respectively.

We now describe level-k players' actions in the Line Game. The standard level-k model assumes that level-0 players are not strategic but are assumed not to play any of the strictly dominated strategies (Chong et al. 2016). Therefore, we first exclude agents who choose

[17] In the KLIPS, the corresponding five options were KRW 10,000, 20,000, 30,000, 40,000, and 50,000. S$1 and KRW 10,000 are equivalent to US$0.75 and US$7.79, respectively, as of Jun 18, 2023.

[18] The position A player is the opponent of the position B player. The position B player is the opponent of the position C player. The position C player is the opponent of the position D player. The position D player is the opponent of the position E player. However, the opponent relationship is asymmetric. For example, the position B player is *not* player A's opponent.

S$10 in position A. Regardless of the actions in the other positions, playing S$10 returns a strictly lower payoff than playing S$50 in position A. Approximately 22% and 31% of the participants in the SLP and KLIPS, respectively, chose this strictly dominated action.[19]

When a level-0 player decides in position B, she is expected to play an action uniformly at random because she does not give the best response to the opponent's action in position A. By contrast, a level-1 player is assumed to believe that the opponent is a level-0 player with a probability of 1. Thus, she believes that the level-0 player plays S$50 in position A and must choose action S$40 in position B. Moreover, any upper-level player also plays S$40 in position B, as they believe that their opponents play S$50 in position A. Therefore, if we observe a subject not choosing S$40 in position B, this subject's choice is *rationalizable* as a level-0 player but not as a level-k player with $k \geq 1$. As such, the first distinctive feature of the level-0 player's action vector in comparison to other players' action vector is the choice of S$40 in position B, as shown in Table 2.[20]

Table 2: Identification of level-k types

	Level-0	Level-1	Level-2	Level-3	Level-4
A	50	50	50	50	50
B	$\neq 40$	40	40	40	40
C	-	$\neq 30$	30	30	30
D	-	-	$\neq 20$	20	20
E	-	-	-	$\neq 10$	10

We then apply the same identification method to the level-k types. For example, given the level-1 players' behavior in position B, the best response of level-2 players is to play S$30 in position C. In addition, since level-1 and level-0 players play the same action in positions A, level-2 players' best response to level-1 players' actions in position B is the same as level-1 players' actions in position B. Therefore, the first distinctive difference between level-1 and level-2 players is the action in position C; that is, not playing S$30 in position C

[19]This reason for exclusion may be considered as the exclusion of subjects who incorrectly answered the comprehension question. In Section C.2, we consider an alternative strategic sophistication measure that includes these subjects. Our results and insights remain unchanged.

[20]This identification method captures only the upper bound of an individual's higher-order rationality, but it is frequently used in the related literature (e.g., Brandenburger et al. 2017; Choi et al. 2022).

is rationalizable as a level-1 player but not as a level-k player with $k \geq 2$. We continue using the same logic to identify level-2 players as those who do not play S$20 in position D.

We observe that the classification of the level-k types in Table 2 closely aligns with the higher order rationality (HOR) measurement described in Choi et al. (2022). Specifically, the HOR order-k types correspond to our level-$(k-1)$ types, provided that $k \geq 1$. The remaining subjects in the dataset who did not choose S$50 in position A are classified as the HOR order-0 type in their paper. One may want to include those HOR order-0 type subjects as level-0 players and redefine the current level-k agents as level $k+1$ agents instead of $k \geq 0$. Indeed, in Appendix C, we find that our main results remain robust for this alternative measurement of level-k. In addition, we consider another measurement constructed by Choi et al. (2022), which deals with the expected payoff based on the subjects' behaviors in the experiment.[21] We find that our results remain robust. We also consider alternative measures of cognitive ability to benchmark their effects on social-distancing behavior against those of the level-k types, as currently defined. Specifically, we included the IQ score obtained from a non-verbal abstract reasoning test[22] and the score obtained in a cognitive empathy test called Reading the Mind in the Eyes.[23]

Table 3 presents the summary statistics of the level-k types and other measures of cognitive ability. Column (1) displays the descriptive statistics of the measured level-k types and cognitive abilities of SLP. More than half the sample demonstrates a level-0. Level-1 accounts for 13%, while level-2 and level-3 represent 7% and 3%, respectively. Interestingly, level-4 shows a significant increase, constituting 20% of the sample. Statistics for both the IQ and cognitive empathy test scores are displayed in a standardized manner. Column (2) shows the descriptive statistics for KLIPS. Level-0 constitutes approximately 67% of the total sample, level-1 and level-2 account for 15% and 8% respectively, while level-3 and level-4 comprise

[21]This variable could be useful in measuring the subjects' strategic sophistication levels as their best-response ability with respect to the actual population.

[22]We use the Intelligence Structure Test (IST) to measure IQ (Beauducel et al. 2010).

[23]This test measures how well someone can understand and empathize with the thoughts and feelings of others (Baron-Cohen et al. 1997).

3% and 7%, respectively. KLIPS data do not collect information on IQ scores but measure cognitive empathy, as in the SLP.

Table 3: Summary statistics of level-k types and other measures of cognitive ability

Data:	SLP (1)	KLIPS (2)
$\mathbf{1}$[Level-k=0]	0.57 (0.50)	0.67 (0.47)
$\mathbf{1}$[Level-k=1]	0.13 (0.33)	0.15 (0.36)
$\mathbf{1}$[Level-k=2]	0.07 (0.26)	0.08 (0.27)
$\mathbf{1}$[Level-k=3]	0.03 (0.18)	0.03 (0.17)
$\mathbf{1}$[Level-k=4]	0.20 (0.40)	0.07 (0.26)
IQ score	0.01 (1.00)	-
Cognitive empathy score	0.01 (1.00)	0.00 (1.00)
Observations	1,608	564

Data source: SLP wave 54 and KLIPS wave 18.
Notes: Standard deviations are in parentheses.

3.2 Data

We use SLP data for the baseline empirical analysis. It has been a monthly online panel survey of nationally representative Singaporeans aged 50–70 years since its launch in July 2015. To measure individuals' social-distancing behaviors, we use information about the frequency of going out. The SLP asked whether individuals left home every day during the last month of each quarter before 2020 (i.e., before the COVID-19 pandemic). After the onset of the COVID-19 pandemic, the SLP asked this question monthly starting in April 2020. Thus, it allows us to examine the short-term dynamics of social-distancing behavior before and after the COVID-19 pandemic while controlling for time-invariant, individual-specific confounding factors by including individual-fixed effects in the empirical analysis. To control for individuals' time-varying characteristics, we include age, age squared, income, and marital status in the regression analysis.

Column (1) in Table 4 presents the summary statistics of the control and dependent variables in SLP. The proportion of respondents who reported going out every day during the period was 72%, and rated their subjective risk aversion on a scale of 0 to 10 at an average of 6.24. The participants had an average age of approximately 60.8 years, with females accounting for 51% and married individuals representing approximately 82%. Additionally, approximately 47% of the participants had completed tertiary education, and the average logarithm of their monthly household income was approximately S$9.49.

Table 4: Summary statistics of dependent and control variables

Datasets:	SLP (1)	KLIPS (2)
1[leaving home daily]	0.72 (0.45)	-
1[increased outdoor activity]	-	0.19 (0.39)
Self-reported risk aversion	6.24 (2.44)	5.29 (2.04)
Age	60.8 (3.61)	47.0 (13.55)
1[female]	0.51 (0.50)	0.54 (0.50)
1[married]	0.82 (0.38)	0.81 (0.39)
1[completed tertiary education]	0.47 (0.50)	0.59 (0.49)
Log(household income)	9.49 (3.33)	8.69 (0.62)
Observations	1,608	564

Data source: SLP wave 54 and KLIPS wave 23.
Notes: Standard deviations are in parentheses.

The SLP data cover individuals with similar age groups (i.e., older individuals) who are at a roughly similar level of risk from COVID-19 and thus share similar payoffs. Otherwise, the payoffs would have been more dispersed if the age group had been extensive. However, we also acknowledge that they are more vulnerable to COVID-19 and thus have a stronger incentive to comply with social-distancing measures than younger individuals. This indicates that our empirical findings based on SLP data may over-emphasize the role of strategic sophistication levels.

To address this concern, we provide evidence of external validity using data from the KLIPS. The KLIPS is a large-scale nationally representative, longitudinal survey of Korean households that has been conducted annually since 1998. Unlike the SLP, the KLIPS collected information on social-distancing behaviors only once in 2020. Thus, we cannot directly compare respondents' behaviors before and after the COVID-19 pandemic. Instead, we use information on self-reported changes in the amount of time spent outdoors. The survey asked about the extent to which the respondents changed the amount of time they spent on those four activities in March 2020 compared to normal periods. We then calculate the average of the changes in these four activities and create a dummy variable indicating whether the average is greater than the median as a proxy for social-distancing behavior.[24]

Column (2) in Table 4 shows the summary statistics of the dependent and control variables of the KLIPS. KLIPS asked how much the respondents' outdoor activities had changed compared with that of before COVID-19.[25] A value of 0.19 means that approximately 19% of respondents increased their outdoor activities compared to before COVID-19. Risk aversion, measured identically as SLP, had an average value of 5.29. On average, the respondents in KLIPS were approximately 14 years younger than those in SLP, with an average age of 47.0. Approximately 54% of the respondents were female and 81% were married. College education was completed by 59% respondents, and the average logarithm of monthly household income in KRW was approximately 8.69.

4 Social-Distancing Behavior by Level-k Types

4.1 Empirical Strategy

To study the effects of strategic sophistication on social-distancing behavior during the COVID-19 pandemic, we compare the changes in individuals' likelihood of leaving home daily before and after the onset of COVID-19 by level-k type. Specifically, we estimate the following DID model:

$$Y_{i,t} = \beta_0 + \beta_1 S_i \cdot COVID\text{-}19_t + \omega_i + \delta_t + X'_{i,t}\lambda + \varepsilon_{i,t},$$

where $Y_{i,t}$ is a measure of individual i's social-distancing behavior (i.e., the likelihood of leaving home daily) in year-month t. S_i is our measure of level-k types. $COVID\text{-}19_t$ is a dummy variable indicating the COVID-19 period beginning February 2020 because the first case of COVID-19 in Singapore was detected on January 23, 2020 (Wong et al. 2020). We control for time-invariant individual characteristics and time-specific shocks by including individual

[24] Since both the SLP and the KLIPS implemented the experiment module to measure level-k types in 2017, we acknowledge a three-year time gap between the social-distancing measures and the level-k type measures.

[25] We use the information on self-reported changes in the amount of time spent on outdoor activities such as (i) watching movies, performances, and exhibitions in a theater, (ii) traveling, (iii) participating in offline religious activities, and (iv) getting together with family members and friends.

and year-month fixed effects, ω_i and δ_t, respectively. $X_{i,t}$ represents a vector of time-varying individual characteristics such as age, age squared, marital status, and household income. $\varepsilon_{i,t}$ denotes the error term.

The coefficient estimate of interest is β_1, which represents the effect of the individuals' level-k types on their daily probability of leaving home. A negative sign indicates that those with a higher level-k type are more likely to engage in social-distancing behavior (i.e., avoid going out) during the COVID-19 period. For statistical inference, we calculate standard errors clustered at the individual level.

In addition, we examine the dynamic effects of the level-k types on social-distancing behaviors during the pandemic for two reasons. First, to interpret β_1 as the causal effect of individuals' strategic sophistication, the trends in home-leaving behavior should be parallel to individuals' level-k type in the absence of a pandemic (i.e., the parallel trend assumption). As an indirect test to validate this assumption, we examine whether the trends of the outcome variable are similar among those with different levels of level-k type prior to the pandemic. Second, it is important for policymakers and researchers to understand dynamic effects because it allows them to design more effective policies by anticipating how policies might evolve and impact different aspects of society over time. By considering dynamic effects, policymakers can make more informed decisions, adapt to changing circumstances, and achieve better outcomes for societies.

To estimate the dynamic behavioral response to the COVID-19 pandemic by level-k, we modify the baseline regression equation by replacing the binary indicator of $COVID\text{-}19_t$ with four dummy variables that indicate six-month intervals: $1[Jan2019 \leq t \leq June2019]$, $1[July2019 \leq t \leq January2020]$, $1[February2020 \leq t \leq June2020]$, and $1[July2020 \leq t \leq January2021]$).[26] We then include the interaction terms between S_i and the four dummy variables. We denote the coefficient estimates of these interaction terms by $\beta_{1,k}$ (where $k = 1, 2, 3, 4$). To test the "parallel pre-intervention trend assumption," we closely exam-

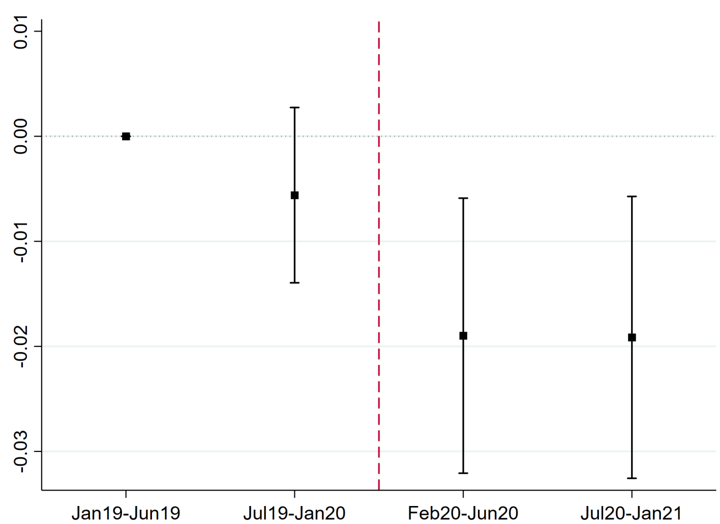
[26]We use $1[Jan2019 \leq t \leq June2019]$ as the reference period.

ine whether $\beta_{1,k}$s are close to zero and statistically insignificant during the pre-COVID-19 period. To demonstrate the persistence of behavioral responses by level-k type, we also present how $\beta_{1,k}$s evolve after the onset of COVID-19.

4.2 Baseline Results

Figure 5 demonstrates the dynamic effects of individuals' strategic sophistication on the probability of leaving home daily with 95% confidence intervals. The red vertical line represents the onset of COVID-19 in Singapore (January 2020). First, $\beta_{1,k}$s values in the year before the pandemic (i.e., between January 2019 and January 2020) are small in magnitude and statistically insignificant. These results indicate that our empirical strategy satisfies the parallel-trend assumption. Second, $\beta_{1,k}$s estimated after the onset of the pandemic are negative and statistically significant at the 5% level. Graphical evidence indicates that individuals with higher level-k types are more likely to reduce their likelihood of going out daily. In addition, this difference in behavioral responses to the COVID-19 pandemic by level-k type appears to persist throughout the first year of the pandemic.

Figure 5: Dynamic effects of strategic sophistication on the probability of leaving home daily during the COVID-19 pandemic



Data source: SLP waves 42–66.
Notes: The square dots represent the estimated $\beta_{1,t}$ coefficients, and caps represent their 95% confidence intervals. The vertical dashed line represents the onset of the COVID-19 pandemic in Singapore.

Although Singapore never imposed full-scale lockdown measures, it enforced school and business closures during the partial lockdown period in April and May 2020.[27] If strategically more sophisticated individuals were more likely to engage in office work, the lockdown could have overemphasized our baseline estimates, because they could have worked from home. This implies that $\beta_{1,3}$ might have been over-estimated during the partial lockdown period. However, the estimated $\beta_{1,4}$ values remain negative and statistically significant at the 5% level. This finding implies that the reduced probability of leaving home daily is less likely to be driven by government restrictions.

We summarize the effects of COVID-19 on social-distancing behavior by level-k type in Table 5. Column (1) shows that a one-level increase in the level-k type measure *reduces* the probability of leaving home daily by 1.6 percentage points after the onset of the COVID-19 pandemic. This estimate is statistically significant at the 1% level.

Table 5: Effects of strategic sophistication on the probability of leaving home daily during the COVID-19 pandemic

Dependent variable:	**1**[Leave home daily]		
	(1)	(2)	(3)
Level-k×COVID-19	-0.016***	-0.016***	
	(0.006)	(0.006)	
1[Level-k=1]×COVID-19			-0.014
			(0.028)
1[Level-k=2 or 3]×COVID-19			-0.032
			(0.032)
1[Level-k=4]×COVID-19			-0.067***
			(0.023)
Fixed effects	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Excluding partial lockdown period	No	Yes	No
Observations	21,897	18,760	21,897
R-squared	0.590	0.611	0.590

Data source: SLP waves 42–66.
Notes: We include individual- and wave-fixed effects and age, age squared, marital status, and household income as control variables in the regression analysis. In column (2), we exclude observations from waves 57 and 58 (April and May 2020) to isolate the effects of the partial lockdown measure. Standard errors are clustered at the individual level and corrected for heteroskedasticity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Column (2) shows that the results remained similar after excluding data from the April

[27] See Kim et al. (2022) for the details of government-imposed lockdown measures in Singapore.

and May 2020 waves (the partial lockdown period). This estimate indicates that a one-level increase in level-k type reduces the probability of leaving home daily by 1.6 percentage points during the pandemic. This estimate is statistically significant at the 1% level.

Column (3) examines the non-linear effects of individuals' strategic sophistication by estimating reductions in the probabilities of leaving home daily among those with level-1, level-2 or 3, and level-4, compared to those with the level-0 type. These estimates indicate the non-linear effects of an individual's strategic sophistication. The degree of social-distancing behavior increases with level-k. Specifically, in contrast to those with level-0 type, individuals with level-1, 2 or 3, and 4 types decrease their probability of leaving home daily during the COVID-19 pandemic by 1.4, 3.2, and 6.7 percentage points, respectively. The final estimate is statistically significant at the 1% level.

In line with Proposition 2-(a), we also conduct a one-sided t-test to examine the monotonicity of social distancing behavior by level-k type in Column (3). The differences in the effects on social distancing behavior are statistically insignificant between level-1 individuals and level-2 or 3 individuals (p-value $= 0.320$), and between level-2 or 3 individuals and level-4 individuals (p-value $= 0.161$). However, the difference between level-1 individuals and level-4 individuals is statistically significant at the 5% level (p-value $= 0.048$).

Our baseline analysis indicates that individuals' behavioral responses during the COVID-19 pandemic can differ according to their heterogeneous strategic sophistication levels under the assumption that our level-k measure represents individuals' strategic sophistication. However, it is also possible that the level-k measures are associated with other cognitive abilities or preferences of individuals. To examine whether our baseline estimates are biased by capturing the effects of other cognitive abilities, we re-estimate the effects of COVID-19 on social distancing behaviors by level-k types after accounting for the effects of other cognitive abilities or preferences.

A recent study Xie et al. (2022) discovered a correlation between a fundamental cognitive skill known as working memory and the extent to which individuals complied with social distancing measures during the COVID-19 pandemic. As these cognitive abilities can be correlated with strategic sophistication levels, we include IQ scores based on non-verbal abstract reasoning tests. Consistent with the findings of previous studies, Column (1) shows that the estimated value of $IQscore \times COVID\text{-}19_t$ is -0.006 and is statistically significant at the 1% level, implying that more intelligent individuals are more likely to reduce their likelihood of leaving home daily. However, the effects of the level-k type remain robust after controlling for the IQ scores. The estimate is -0.012 and is statistically significant at the 5% level. This result indicates that strategic sophistication levels play an independent role in affecting individuals' social-distancing behaviors during the COVID-19 pandemic.

Several studies have documented disparities in the impact of COVID-19 across educational attainment levels (e.g., Case and Deaton 2021; Daly et al. 2020). Since educational level can also be associated with strategic sophistication, we include educational attainment as an additional control variable. Consistent with the findings of previous studies, Column (2) demonstrates that individuals who have higher educational attainments (i.e., those who completed tertiary education) are 7.4 percentage points more likely to practice social distancing behavior than those with lower levels of education. However, the coefficient value for the interaction between level-k types and $COVID\text{-}19_t$ remains statistically significant even after accounting for the effects of education.

Additionally, cognitive empathy, which is the ability to recognize others' mental states, can positively influence social distancing behaviors (e.g., Pfattheicher et al. 2020; Xu and Cheng 2021). As cognitive empathy might be related to strategic behavior, we control for cognitive empathy test scores in the regression analysis. Consistent with the conjecture that cognitive empathy test scores capture pro-social behavior, Column (3) indicates that those with higher cognitive empathy test scores are more likely to comply with social-distancing behavior during the pandemic, although the estimate is statistically insignificant. Nonetheless, the estimates of heterogeneous social-distancing behaviors by level-k type remain similar.

Individuals' risk preferences can be an important factor in predicting their compliance

Table 6: Effects of strategic sophistication on the probability of leaving home daily during the COVID-19 pandemic *while controlling for other cognitive skill measures and risk preference*

Dependent variable:	**1**[Leave home daily]				
	(1)	(2)	(3)	(4)	(5)
Level-k×COVID-19	-0.012**	-0.014**	-0.014**	-0.015***	-0.011**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
IQ score×COVID-19	-0.006***				-0.004*
	(0.002)				(0.002)
Completed tertiary education×COVID-19		-0.074***			-0.065***
		(0.018)			(0.018)
Cognitive empathy×COVID-19			-0.009		-0.009
			(0.009)		(0.009)
Self-rated risk aversion×COVID-19				0.007**	0.005
				(0.004)	(0.004)
Fixed effects	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes
Observations	21,897	21,897	21,897	21,897	21,897
R-squared	0.593	0.594	0.593	0.593	0.594

Data source: SLP waves 42–66.

Notes: We include individual and monthly fixed effects and age, age squared, marital status, and household income. Additionally, we include the interaction terms between COVID-19 with control variables, namely age, gender, marital status, and household income in the regression analysis. Standard errors are clustered at the individual level and corrected for heteroskedasticity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

with social distancing measures or risk-avoiding behaviors during a pandemic (e.g., Chan et al. 2020; Sheth and Wright 2020). Column (4) shows that our estimate of the effects of level-k types is robust to including our self-rated risk aversion measure. However, we find that risk-averse individuals are more likely to leave home daily during the pandemic. This result may seem puzzling and counterintuitive; however, from a game-theoretic perspective, it is not surprising. Note that the payoff matrix in our theoretical framework is a variant of the Stag Hunt game. In a Stag Hunt game, there is a pure-strategy Nash equilibrium that is risk-dominant (Harsanyi and Selten 1988). Experimental evidence shows that risk-averse individuals are more likely to play the action for the risk-dominant Nash equilibrium (e.g., Dal Bó et al. 2021). In our game, the risk-dominant Nash equilibrium corresponds to strategy profile (NC, NC). The results in Column (4) indicate that individuals behaved during the pandemic, as predicted by the theory.

In Columns (1)–(4), we examine the pairwise relationships between level-k types and the measures of other cognitive abilities and preferences. The result is similar when we examine their relationships jointly by including all four interaction terms in the regression analysis in Column (5). If the two variables measure the same information but to varying degrees, then including other measures of cognitive ability would either nullify the influence of level-k or render the effects of both variables statistically insignificant. However, Table 6 shows that the effect of level-k remains robust after we control for the effects of other measures of individuals' cognitive abilities and preferences. This result suggests that the level-k type assesses distinct cognitive abilities, which can significantly influence an individual's decision to exhibit social-distancing behavior.

4.3 Additional Analysis Using the KLIPS Data

As stated in Section 3.2, a limitation of the SLP data is that they only cover relatively older individuals. Because older individuals are more vulnerable to the coronavirus, our baseline results may have over-emphasized the true effects of individuals' strategic sophistication. To address this limitation, we use data from the KLIPS, which represents the entire adult population in South Korea and contains an identical set of cognitive ability measures such as level-k types, the cognitive empathy test, and subjective risk preferences. Unfortunately, the KLIPS does not provide information on IQ scores. Thus, we use backward induction thinking ability as a proxy.[28] However, we acknowledge that the sample size of the KLIPS is smaller than that of the SLP, and we can only conduct a cross-sectional analysis, as the outcome variable was asked once as part of the special COVID-19 module.

Table 7 shows consistent evidence that the level-k type is closely associated with social-distancing behavior. In 2020, the respondents were asked whether they had increased, decreased, or not changed their outdoor activities during the pandemic. We construct a dummy variable to measure whether participants increased their outdoor activities. Column (1) indicates that a one-level increase in level-k type reduces the probability of increasing outdoor activities by 3.4 percentage points, and the estimate is statistically significant at the 1% level. We sequentially add more control variables to Columns (2)–(4) and find that the base-

[28]See Choi et al. (2022) for details.

Table 7: Effects of strategic sophistication on the probability of outdoor activities during the COVID-19 pandemic *using the KLIPS data*

Dependent variable:	**1**[Increased outdoor activities]				
	(1)	(2)	(3)	(4)	(5)
Level-k	-0.034***	-0.032***	-0.032***	-0.030***	
	(0.011)	(0.011)	(0.011)	(0.011)	
1[Level-k=1]					-0.068
					(0.044)
1[Level-k=2 or 3]					0.002
					(0.057)
1[Level-k=4]					-0.153***
					(0.043)
Other controls 1	Yes	Yes	Yes	Yes	Yes
Other controls 2	No	Yes	Yes	Yes	Yes
Other controls 3	No	No	Yes	Yes	Yes
Other controls 4	No	No	No	Yes	Yes
Observations	564	564	564	564	564
R-squared	0.013	0.038	0.039	0.055	0.059

Data source: KLIPS, waves 20, and 23.
Notes: Other controls 1 includes age, age squared, marital status, and living with aged 0–6 years. Other controls 2 includes female and college graduate and above. Other controls 3 includes household income. Other controls 4 includes cognitive empathy score and risk aversion. Standard errors in parentheses are corrected for heteroskedasticity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

line estimate remains robust.[29] As shown in Column (5), we consider non-linear effects and find evidence consistent with that of SLP: the change in social-distancing behavior is mainly driven by those with the highest level-k type. In summary, the results obtained from the SLP sample provide consistent evidence that the restricted age range of the sample is unlikely to cause an upward bias in our baseline analysis.

5 Conclusion

We study a real-world example of individuals' interactions via the lens of level-k theory in the context of social distancing behavior during the early stages of the COVID-19 pandemic. We build a two-person weakest-link public goods game with the private cost of social-distancing actions. In the game, a player optimizes behavior based on their belief that the other player's strategic sophistication level (level-k type) is lower than their level. The likelihood of a player displaying social-distancing behavior increases as the level-k type in-

[29] Table C1 reports full regression results.

creases, under a reasonable assumption. We provide empirical evidence that our theoretical hypothesis is consistent with data from nationally representative samples. Our main results are robust to the alternative specifications for both theoretical and empirical analyses, and provide novel evidence that level-k theory is useful for understanding individuals' collective action in real-world settings.

Our analysis implicitly assumes that the level-k type of an individual is stable; that is, the level-k type identified in the economic experiment (i.e., the Line Game) is identical to the level-k type in the social-distancing behavior game. This consistency problem of strategic sophistication in level-k models has been recognized in the literature (e.g., Cooper et al. 2018; Georganas et al. 2015). Future research could investigate whether individuals' strategic sophistication level is stable across different types of games with real-world applications.

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A Proofs

Proof of Proposition 1

Proof. We prove the result for a generalized cognitive hierarchy model, because it contains a standard level-k model as a special case. Each player is of type k (i.e., level-k), where k represents the strategic sophistication level. A type k player believes that the opponent is of type $k' \in \{0, 1, \dots, k-1\}$ with probability $P_k(k')$. For example, if $P_k(k-1) = 1$ and $P_k(j) = 0$ for all $j < k-1$, then type k player is a level-k player in the main text. For the generalized cognitive hierarchy model (Chong et al. 2016), we first let $P : \mathbb{N}_0 \to \mathbb{R}$ be the distribution of types, where $P(k)$ is the probability that a randomly chosen player is of type $k \in \mathbb{N}_0$. Then, for each $k' \in \{0, \dots, k-1\}$, $P_k(k')$ can be defined as

$$P_k(k') = \frac{P(k')}{\sum_{j=0}^{k-1} P(j)}.$$

Thus, $P_k(j)$ is the conditional probability generated from P given the belief that the opponent's cognitive type is at most $k-1$. Note that for these two examples, the type 1 player believes that the opponent is type 0 with a probability of 1.

For each type k with $k \geq 1$, let π_k be the probability of a type k player playing C. Let μ_k be the expectation of a type k player regarding the probability of another player choosing action C. With this modified notation, the statement in the proposition can be rewritten as

"Let $\pi_0 \in (0, 1)$ be the probability that a level-0 player chooses action C. For any $k \geq 1$, a level-k player plays a cutoff strategy with a cutoff cost c_k, where c_k is recursively defined as $c_k = \mu_k$ with $\mu_k = \pi_0$ if $k = 1$ and $\mu_k = \sum_{i=1}^{k-1} \pi_i P_k(i)$ if $k \geq 2$."

Because the proof is straightforward, we omitted it. ■

Proof of Proposition 2

Proof.

Proof of (a). Suppose that $\pi_0 < \pi^*$. To demonstrate that π_k is strictly increasing in k, it is sufficient to demonstrate that μ_k is also strictly increasing in k. In the following section, we prove this using the induction principle.

First, it follows that:

$$\mu_1 = \pi_0 < \pi_0 P_2(0) + F(\pi_0) P_2(1) = \mu_2,$$

where the strict inequality follows the single-crossing assumption.

Suppose that $\mu_k < \mu_{k+1}$. To demonstrate that $\mu_{k+1} < \mu_{k+2}$, we observe that $\mu_{k+1} = \sum_{i=0}^{k} \pi_i P_{k+1}(i)$ and $\mu_{k+2} = \sum_{j=0}^{k+1} \pi_j P_{k+2}(j)$. Then, we find that

$$\begin{aligned}
\mu_{k+1} - \mu_{k+2} &= \sum_{i=0}^{k-1} \pi_i \left(P_{k+1}(i) - P_{k+2}(i)\right) + \pi_k \left(P_{k+1}(k) - P_{k+2}(k)\right) - \pi_{k+1} P_{k+2}(k+1) \\
&< \pi_k \sum_{i=0}^{k} \left(P_{k+1}(i) - P_{k+2}(i)\right) - \pi_{k+1} P_{k+2}(k+1) \\
&= \pi_k \left(1 - \sum_{i=0}^{k} P_{k+2}(i)\right) - \pi_{k+1} P_{k+2}(k+1) \\
&= \left(\pi_k - \pi_{k+1}\right) P_{k+2}(k+1) < 0.
\end{aligned}$$

Therefore, this statement is proven.

Proof of (b). Suppose that $\pi_0 > \pi^*$. The induction principle is used in the proof of (a). Again, this suffices to demonstrate that μ_k strictly decreases in k. First, it follows that:

$$\mu_1 = \pi_0 > \pi_0 P_2(0) + F(\pi_0) P_2(1) = \mu_2,$$

where the strict inequality follows the single-crossing assumption.

Suppose that $\mu_k > \mu_{k+1}$. To demonstrate that $\mu_{k+1} > \mu_{k+2}$, we observe that $\mu_{k+1} = \sum_{i=0}^{k} \pi_i P_{k+1}(i)$ and $\mu_{k+2} = \sum_{j=0}^{k+1} \pi_j P_{k+2}(j)$. Then, we find that

$$\begin{aligned}
\mu_{k+1} - \mu_{k+2} &= \pi_0 \left(P_{k+1}(0) - P_{k+2}(0)\right) + \sum_{i=1}^{k} \pi_i \left(P_{k+1}(i) - P_{k+2}(i)\right) - \pi_{k+1} P_{k+2}(k+1) \\
&> \pi_0 \sum_{i=0}^{k} \left(P_{k+1}(i) - P_{k+2}(i)\right) - \pi_{k+1} P_{k+2}(k+1) \\
&= \pi_0 \left(1 - \sum_{i=0}^{k} P_{k+2}(i)\right) - \pi_{k+1} P_{k+2}(k+1)
\end{aligned}$$

$$= (\pi_0 - \pi_{k+1}) \, P_{k+2}(k+1) > 0.$$

Therefore, this statement is proven.

Proof of (c). Suppose that $\pi_0 = \pi^*$. Again, we use the principles of induction. It suffices to show that μ_k is a constant. First, it directly follows because $F(\pi^*) = \pi^*$,

$$\mu_1 = \pi^* = \pi^* P_2(0) + F(\pi^*) P_2(1) = \mu_2.$$

Suppose that $\mu_k = \mu_{k+1}$. To demonstrate that $\mu_{k+1} = \mu_{k+2}$, we observe that $\mu_{k+1} = \sum_{i=0}^{k} \pi_i P_{k+1}(i)$ and $\mu_{k+2} = \sum_{j=0}^{k+1} \pi_j P_{k+2}(j)$. Then, we find that

$$\begin{aligned}\mu_{k+1} - \mu_{k+2} &= \pi^* \left(P_{k+1}(0) - P_{k+2}(0)\right) + \sum_{i=1}^{k} \pi^* \left(P_{k+1}(i) - P_{k+2}(i)\right) - \pi_{k+1} P_{k+2}(k+1) \\ &= \pi^* \left(1 - \sum_{i=0}^{k} P_{k+2}(i)\right) - \pi_{k+1} P_{k+2}(k+1) = (\pi^* - \pi_{k+1}) \, P_{k+2}(k+1) = 0.\end{aligned}$$

Therefore, this statement is proven. ■

Proof of Proposition 3

Proof. We assume that F first-order stochastically dominates G. Let π_0 be the probability of choosing C for level-0 players. Let $\pi_k(\theta)$ be the type k player's probability of choosing action C under the distribution $\theta \in \{F, G\}$. Then, it would be sufficient to demonstrate that $\mu_k(G) \geq \mu_k(F)$ for all k, and that equality holds only for $k = 1$. First, we determine that $\mu_1(G) = \pi_0 = \mu_1(F)$.

We now show that $\mu_2(G) > \mu_2(F)$. To see why, we directly calculated the

$$\mu_2(G) = \pi_0 P_2(0) + G(\pi_0) P_2(1) > \pi_0 P_2(0) + F(\pi_0) P_2(1) = \mu_2(F).$$

This strict inequality implies $\pi_2(G) > \pi_2(F)$.

Suppose $\mu_k(G) > \mu_k(F)$ and $\pi_k(G) > \pi_k(F)$. Then, it follows that

$$\mu_{k+1}(G) = \sum_{i=0}^{k} \pi_i(G) P_{k+1}(i) > \sum_{i=0}^{k-1} \pi_i(F) P_{k+1}(i) = \mu_{k+1}(F),$$

This implies $\mu_{k+1}(G) > \mu_{k+1}(F)$. Therefore, this proposition is proven. ■

B General Payoff Structure

In the main text, we consider a more general game payoff structure. Because the game is symmetric, we focus on player 1's payoff without loss of generality. We denote c as the contribution cost for player 1. To normalize the payoffs, we assume that player 1 has zero utility. Additionally, because player 1 benefits from player 2's contribution, we let $v_L \geq 0$ represent utility when player 2 contributes but player 1 does not. When player 1 contributes but player 2 does not, player 1 obtains a utility of $v_M \geq v_L$. Evidently, the best scenario for the agent is when both players contribute. In this case, we denote $v_H > v_M$ as the utility of the agent.[30] Note that if $v_L = v_M = 0$, the payoff structure becomes identical to the payoff matrix in Table 1 in the main text.

Table A1: The general payoff matrix

		player 2: NC	player 2: C
player 1	NC	0	v_L
	C	$v_M - c$	$v_H - c$

We assume $v_H \in (v_L + v_M, \bar{c})$. First, the assumption $\bar{c} > v_H$ implies that when the social distancing cost is significantly high, it is more beneficial to pursue free-riding utility: $v_H - \bar{c} < v_L$. For example, consider an individual requiring regular renal dialysis who cannot discontinue hospital visits even during the pandemic. Second, if $v_H > v_L + v_M$, then the marginal (expected) benefit from contribution increases with the other player's probability of contribution (i.e., strategic complements).[31] To see this, note that for a given belief $\pi \in (0, 1)$ and cost of contribution c, player plays C if and only if $v_M + \pi(v_H - (v_L + v_M)) > c$. The left-hand side captures the marginal benefit from the contribution, and its partial derivative with respect to π is strictly positive if the assumption holds. In the remainder of this analysis,let

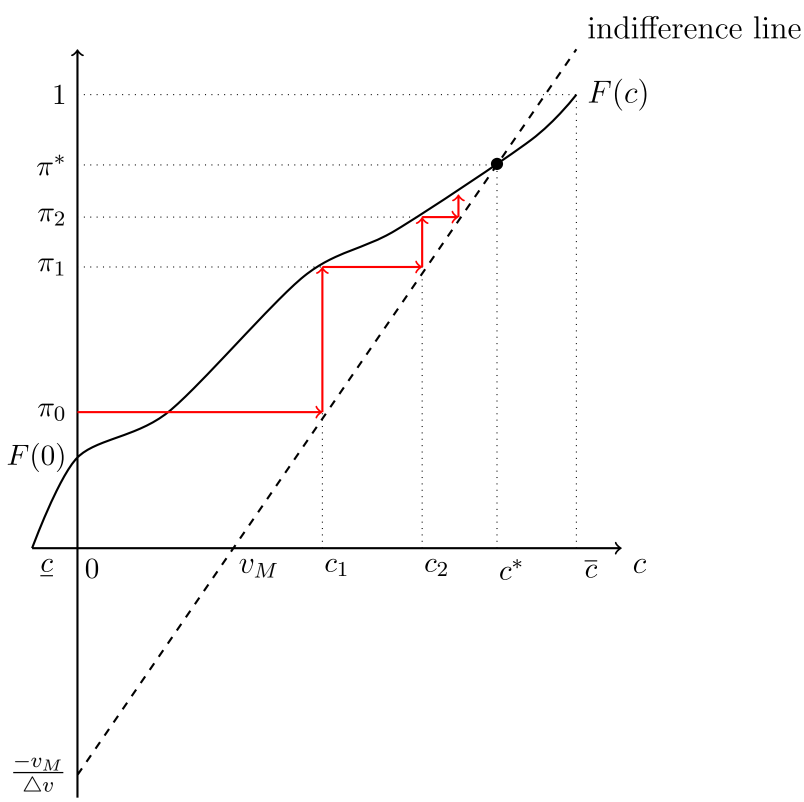
[30] Wearing a mask alone significantly reduces the risk of infection compared to situations where a person does not wear a mask while others do.

[31] For example, during the COVID-19 pandemic, it was generally better for both individuals to wear masks together. This creates a barrier against respiratory droplets containing the virus, preventing their release into the air or inhalation by others.

$\triangle v = v_H - (v_L + v_M)$.

Here, we show that the probability of choosing action C strictly increases in level-k type if the level-0 player's likelihood of choosing action C is relatively low (Proposition 2). Figure 6 describes the situation in which π_0 is slightly greater than $F(0)$. Given this level-0 player's behavior, the level-1 player's cutoff cost c_1 is determined as $c_1 = v_M + \pi_0 \triangle v$. A level-2 player believes that the level-1 player plays C with probability $\pi_1 = F(v_M + \pi_0 \triangle v)$. The corresponding cutoff cost c_2 is $c_2 = v_M + F(v_M + \pi_0 \triangle v)\triangle v$. Since $\pi_0 < \pi^*$, we have $c_1 < c^*$; thus, we also have $\pi_1 < \pi^*$ and $c_2 < c^*$. Therefore, we obtain $c_1 < c_2$; when π_0 is relatively low, strategic sophistication generates a best-response dynamic in which a level-2 player's cutoff cost c_2 is strictly greater than the level-1 player's cutoff cost c_1.

Figure 6: Illustration of increasing cutoff costs at strategic sophistication levels



As in the main text, by the induction principle, the same increasing property emerges for higher level-k types. Consequently, we obtain the property that the sequence of cutoff costs $\{c_k\}_{k \geq 1}$ strictly increase as the strategic sophistication parameter k increases. Finally, the probability of choosing action C increases as level k increases.

The opposite decreasing dynamic arises when π_0 is relatively high because $\pi_0 > \pi^* = F(c^*)$. Furthermore, our previous analysis of how players' behaviors and the resulting best-response dynamics respond to a change in the cost distribution remain qualitatively the same.

C Additional Tables and Figures

C.1 Full Tables

Table C1: The full regression results of Table 7

Dependent variable:	**1**[Increased outdoor activities]				
	(1)	(2)	(3)	(4)	(5)
Level-k	-0.034***	-0.032***	-0.032***	-0.030***	
	(0.011)	(0.011)	(0.011)	(0.011)	
1[Level-k=1]					-0.068
					(0.044)
1[Level-k=2 or 3]					0.002
					(0.057)
1[Level-k=4]					-0.153***
					(0.043)
Age	-0.003	-0.002	-0.003	-0.002	-0.002
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Age squared/1000	0.032	-0.007	0.002	-0.013	-0.011
	(-0.091)	(-0.091)	(-0.091)	(-0.094)	(0.093)
Marital status	-0.043	-0.034	-0.042	-0.043	-0.036
	(0.067)	(0.066)	(0.068)	(0.067)	(0.066)
Living with children aged 0-6years	-0.006	0.008	0.012	0.019	0.023
	(0.053)	(0.052)	(0.053)	(0.052)	(0.052)
Female		-0.061*	-0.060*	-0.067**	-0.070**
		(0.034)	(0.034)	(0.034)	(0.034)
College graudate and above		-0.136***	-0.140***	-0.144***	-0.145***
		(0.042)	(0.042)	(0.042)	(0.042)
Household income			0.022	0.014	0.014
			(0.026)	(0.026)	(0.026)
Cognitive empathy score				-0.007	-0.006
				(0.018)	(0.018)
Risk aversion				0.024***	0.024***
				(0.008)	(0.008)
Observations	564	564	564	564	564
R-squared	0.013	0.038	0.039	0.055	0.059

Data source: KLIPS, waves 18, 20, and 23. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C.2 Robustness Checks by Alternative Measurement 1

Definition. The primary measurement considered in the main text excludes the subjects who chose S$10 in position A. One way to measure the strategic sophistication is to include those subjects as level-0 players and step up the other depth levels by one level. The new measurement with this inclusion is identical to the HOR order in Choi et al. (2022). The resulting level-k types consist of six levels, as Table C2 summarizes.

Table C2: Identification of level-k types

	Level-0	Level-1	Level-2	Level-3	Level-4	Level-5
A	$\neq 50$	50	50	50	50	50
B	-	$\neq 40$	40	40	40	40
C	-	-	$\neq 30$	30	30	30
D	-	-	-	$\neq 20$	20	20
E	-	-	-	-	$\neq 10$	10

Results. We consider the same econometric model as in the main text and summarize the effects of individuals' strategic sophistication on social-distancing behavior during the COVID-19 pandemic in Table C3. The results remain similar to those of the baseline analysis when an alternative measure of strategic sophistication is used. Column (1) shows that a one-level increase in the level-k type measure reduces the probability of leaving home daily by 1.8 percentage points after the onset of the COVID-19 pandemic. This estimate is statistically significant at the 1% level. Because the average probability of leaving home daily among individuals at level-0 is 22%, our estimate indicates that the likelihood would have been 13% among those at level-5. Column (2) shows that after excluding data from the April and May 2020 waves (the partial lockdown period), a one-level increase in the level-k measure reduce the probability of leaving home daily by 1.8 percentage points during the pandemic. This finding is statistically significant at the 1% level.

In Column (3), we examine the non-linearity in the effects of strategic sophistication. We estimate reductions in the probabilities of leaving home daily among those with level-1, level-2 or 3, and level-4 or 5 compared with that of level-0. The estimates indicate the non-

Table C3: Effects of strategic sophistication on the Probability of Leaving Home Daily during the COVID-19 pandemic

Dependent variable:	**1**[Leave home daily]		
	(1)	(2)	(3)
Level-k×COVID-19	-0.018***	-0.018***	
	(0.005)	(0.005)	
1[Level-k=1]×COVID-19			-0.032*
			(0.019)
1[Level-k=2 or 3]×COVID-19			-0.053**
			(0.025)
1[Level-k=4 or 5]×COVID-19			-0.092***
			(0.024)
Fixed effects	Yes	Yes	Yes
Other controls	Yes	Yes	Yes
Including partial lockdown period	Yes	No	Yes
Observations	28,244	24,195	28,244
R-squared	0.601	0.624	0.601

Data source: SLP waves 42-66.
Notes: We include individual and monthly fixed effects and age, age squared, marital status, and household income in the regression analysis. In column (2), we exclude observations from waves 57 and 58 (April 2020 and May 2020) to isolate the effects of Circuit Breaker. Standard errors are clustered at the individual level and corrected for heteroskedasticity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

linear behavioral responses by level-k types. In particular, compared with level-0, individuals with level-1, 2 or 3, and 4 or 5 types decrease the probability of leaving home daily during the COVID-19 pandemic by 3.2, 5.3, and 9.2 percentage points, respectively. The estimates are statistically significant at the 10%, 5% and 1% levels, respectively.

In Table C4, we examine whether our baseline results remain robust after accounting for heterogeneous behavioral responses using measures of IQ scores, education level, cognitive empathy, and risk preference. Column (1) shows that the estimated value of $IQscores \times COVID\text{-}19_t$ is -0.005 and is statistically significant at the 1% level. This result implies that more intelligent individuals are more likely to reduce the likelihood of leaving their homes daily. However, the heterogeneous behavioral response at level-k remains intact. The estimate is -0.015 and is statistically significant at the 1% level. This indicates that strategic sophistication plays an independent role in affecting individuals' social-distancing behavior during the COVID-19 pandemic.

The results are similar when adding the interaction terms of the measures of education

Table C4: Effects of strategic sophistication on the probability of leaving home daily *while controlling for other cognitive skill measures, and risk averseness*

Dependent variable:	**1**[Leave home daily]				
	(1)	(2)	(3)	(4)	(5)
Level-k×COVID-19	-0.015***	-0.016***	-0.016***	-0.017***	-0.014***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
IQ ×COVID-19	-0.005***				-0.003
	(0.002)				(0.002)
Tertiary education×COVID-19		-0.067***			-0.057***
		(0.016)			(0.016)
Cognitive empathy×COVID-19			-0.009		-0.009
			(0.008)		(0.008)
Risk aversion×COVID-19				0.008***	0.006**
				(0.003)	(0.003)
Fixed effects	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes
Observations	28,244	28,244	28,244	28,244	28,244
R-squared	0.603	0.604	0.603	0.604	0.604

Data source: SLP waves 42-66.

Notes: We include individual and monthly fixed effects and age, age squared, marital status, and household income. Additionally, we include interaction terms between COVID-19 with control variables, namely age, gender, marital status, and household income in the regression analysis. Standard errors are clustered at the individual level and corrected for heteroskedasticity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

level, cognitive empathy, and risk aversion to $COVID\text{-}19_t$ in Columns (2), (3), and (4). The estimates of heterogeneous social-distancing behaviors by level-k remain similar. Column (2) demonstrates that individuals with higher education levels (i.e., completed tertiary education) are 6.7 percentage points more likely to practice distancing than those with lower levels of education. In addition, Column (3) shows that the estimate of the interaction term between cognitive empathy and $COVID\text{-}19_t$ is negative, but statistically insignificant. Meanwhile, we find that more risk-averse individuals are more likely to leave home daily during the pandemic, as shown in Column (4). These results are similar when all four additional interaction terms are included in the regression analysis in Column (5). This suggests that the level-k type independently and significantly influences an individual's decision to exhibit social-distancing behavior.

C.3 Robustness Check by Alternative Measurement 2

Definition. We also consider another measure of strategic sophistication. As an alternative way to measure how well an individual performs in a Line Game, we calculate the expected payoffs (in S$) based on the subjects' actual choices in the experiment. Specifically, a subject's expected payoff is calculated based on her choice matched with the *empirical distribution* of her opponent's choices observed in our data following Choi et al. (2022). First, we calculate the empirical choice distribution for each position from the SLP data. Second, for a given subject, we match a subject's choice in each position with the empirical choice distribution of the opponent's position. Finally, we compute the average expected payoffs for all five positions.

Results. Table C5 presents results that are qualitatively similar to the baseline analysis. Column (1) shows that an S$1 increase in the expected payoff decreases the likelihood of leaving home daily by 0.04 percentage points. As the standard deviation of the expected payoffs is S$55.17, the estimate indicates that the probability of leaving home daily reduces by 2.21 percentage points when the expected payoff increases by one SD.[32] This estimate is statistically significant at the 5% level. The results remain robust when data from the partial lockdown period are excluded.

[32]The mean of the expected payoff is S$276.4.

Table C5: Effects of the strategic sophistication on the probability of leaving home daily during the COVID-19 pandemic *using expected payoff of the Line Game as an alternative measurement*

Dependent variable:	**1**[Leave home daily] (1)	(2)
Expected payoffs×COVID-19	-0.0004**	-0.0004**
	(0.0002)	(0.0002)
Including partial lockdown period	Yes	No
Observations	21,897	18,760
R-squared	0.590	0.611

Data source: SLP waves 42–66.

Notes: We include individual and monthly fixed effects and age, age squared, and marital status in the regression analysis. In column (2), we exclude observations from waves 57 and 58 (April and May 2020) to isolate the effects of the partial lockdown (called the Circuit Breaker). Standard errors are clustered at the individual level and corrected for heteroskedasticity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.