The More the Better? The Influence of Peer Group Size on Financial Decision Making

by

Dongli Hu

A thesis accepted and approved in partial fulfillment of the

requirements for the degree of

Master of Science

in Economics

Dissertation Committee:

Michael Kuhn, Chair

Alfredo Burlando, Co-chair

University of Oregon

Winter 2025

THESIS ABSTRACT

Dongli Hu

Master of Science in Economics

Title: The More the Better? The Influence of Peer Group Size on Financial Decision Making

We examine how peer group size influences financial decision-making using a two-stage experiment with two investment tasks conducted over three rounds. Participants initially make individual financial choices before being assigned to small (2-person) or large (4-person) peer groups, where they discuss and make subsequent decisions. By systematically varying group size, we assess whether exposure to more peers improves decision quality through information aggregation or hinders it due to coordination challenges. We employ a difference-in-differences approach to measure the causal impact of group size on investment behavior. Comparing outcomes across rounds, we evaluate whether larger groups enhance decision-making or if smaller groups provide a more effective environment for learning and adaptation. This study contributes to the understanding of peer effects in financial choices, shedding light on whether "the more, the better" or "less is more" when it comes to social influence in investment decisions.

TABLE OF CONTENTS

Chapter Page

I. THE MORE THE BETTER? THE INFLUENCE OF PEER GROUP SIZE ON FINANCIAL DECISION MAKING . . . 7

1.1. Introduction . . . 7

1.2. Literature Review . . . 9

1.2.1. Peer Influence in Financial Decision-Making . . . 10

1.2.2. Herd Behavior and Social Influence . . . 10

1.2.3. The Role of Group Size in Decision-Making . . . 11

1.3. Experimental Design . . . 12

1.3.1. Design Structure . . . 12

1.3.2. Financial choices . . . 15

1.3.2.1. Task 1: Stated investment preferences . . . 15

1.3.2.2. Task 2: Revealed lottery preferences . . . 18

1.3.3. Treatment Variation . . . 20

1.3.4. Hypotheses . . . 21

1.4. Implementation Plan . . . 23

REFERENCES CITED . . . 24

LIST OF FIGURES

Figure Page

1. Layout of Study 14

2. Portfolio Allocation 17

3. Top 5 Single Stocks 18

4. Rabin and Weizsäcker (2009) Example Decisions 19

LIST OF TABLES

Table		Page
1.	Map from Coefficients to Means	21
2.	Effects of Group & Size	21

CHAPTER I

THE MORE THE BETTER? THE INFLUENCE OF PEER GROUP SIZE ON FINANCIAL DECISION MAKING

1.1 Introduction

According to the Survey of Consumer Finances, 99% of U.S. families owned at least one financial asset in 2022, and 58% held stocks through either direct or indirect investments.[1] This marks an increase from 53% in 2019 and 52% in 2016, highlighting a growing engagement with financial markets. As stock market participation expands—particularly among retail investors using trading apps to select individual assets—the question of how individuals make investment decisions has never been more relevant.

When faced with the decision to invest in the stock market, many individuals may feel uncertain about selecting the "right" assets, especially when relying solely on historical price trends displayed in trading apps like Robinhood. In such cases, a natural response is to seek guidance from someone with more experience—perhaps a relative or friend who has been actively investing for years. This highlights a fundamental aspect of financial decision-making: when individuals lack sufficient information, they likely turn to peers for advice. Peer influence may play a crucial role in shaping investment choices, particularly when investors navigate unfamiliar financial markets.

While prior research has examined the role of group size in decision-making—such as the impact of corporate board size on firm outcomes Jenter, Schmid, and Urban (2023)—less is known about how the size of a peer group influences individual financial decisions. Does exposure to a larger group lead

[1] https://www.federalreserve.gov/econres/scfindex.htm

to better investment choices by providing access to more diverse information? Or does it instead create inefficiencies, as conflicting opinions make it harder to extract useful insights? In other words, do investors benefit from "the wisdom of the crowd," or do they struggle to navigate an overload of perspectives? This study seeks to experimentally test how the number of peers in a group shapes the strength of peer effects in investment decisions, shedding light on whether larger peer groups enhance or hinder financial decision-making.

This study employs a controlled experimental approach to examine how the size of peer groups influences financial decision-making. Participants will engage in a two-stage experiment involving two different types of investment tasks across three decision rounds. The first task will elicit stated investment preferences, allowing participants to construct hypothetical portfolios. The second task will reveal biased decision making through incentivized lottery choices.

The core treatment variation involves exposing participants to peer groups of different sizes and measuring how this exposure influences their decisions. Initially, participants will make investment choices individually. In subsequent rounds, they will be placed in either small (2-person) or large (4-person) peer groups, where they can discuss their decisions before making a final choice. To isolate the impact of group size, participants will experience both small and large groups in different rounds.

The study aims to answer key questions: Does exposure to more peers improve decision-making by aggregating information, or does it hinder it by increasing noise and coordination challenges? Is there an optimal group size that maximizes financial decision quality? By implementing a difference-in-difference analytical approach, we will assess whether peer effects grow stronger or weaker as group size changes.

The results of this study will contribute to our understanding of peer influence in financial decision-making, offering insights into the trade-offs between group size, information aggregation, and behavioral biases.

1.2 Literature Review

Financial decision-making is complex, requiring individuals to weigh risks, returns, and external influences. A growing body of research highlights the role of peer effects in shaping investment behavior. Individuals often rely on social networks to guide their financial choices, particularly in situations of uncertainty. This section reviews key literature on peer influence in financial decision-making, with a focus on the role of group size.

More broadly, however, peer effects have been widely studied across various domains beyond financial decision-making, highlighting the pervasive influence of social interactions on individual behavior. In education, researchers have documented how peer ability affects academic outcomes, with students performing better when surrounded by high-achieving classmates (Henderson, Mieszkowski, & Sauvageau, 1978; Zimmerman, 2003)). Similarly, studies on neighborhood effects show that individuals' socioeconomic and behavioral outcomes are shaped by their residential environment, with evidence that growing up in disadvantaged neighborhoods can negatively impact long-term earnings, education, and even teenage pregnancy rates (Case & Katz, 1991; Jenter et al., 2023; Katz, Kling, & Liebman, 2001-05). These findings suggest that peer influence extends far beyond finance, affecting decision-making in diverse settings. Understanding these broader patterns of peer effects provides a useful framework for examining how social interactions shape investment behavior, particularly when individuals rely on their networks for financial information and guidance.

1.2.1 Peer Influence in Financial Decision-Making.

Behavioral finance suggests that investors often rely on their peers when making investment decisions, particularly when facing uncertainty. Barber and Odean (2013) provide evidence that investors are influenced by their immediate environment, tending to hold stocks from their employers or companies located nearby. Ouimet and Tate (2020) further demonstrate that peer networks significantly shape investment behavior, finding that employees in the same firm are more likely to participate in employee stock purchase plans (ESPPs) if their colleagues do the same.[2]

Beyond direct workplace interactions, word-of-mouth communication plays a critical role in disseminating investment information. Ellison and Fudenberg (1995) suggest that informal discussions can lead individuals to make similar financial choices, as they adopt the behaviors of those around them. This type of information flow, while useful, may also lead to suboptimal decision-making if individuals fail to independently verify the quality of the information received.

1.2.2 Herd Behavior and Social Influence.

A related phenomenon in peer-influenced financial decision-making is herd behavior. Banerjee (1992) develops a theoretical model showing that individuals tend to imitate the decisions of those who acted before them, even when they possess private information suggesting an alternative course of action. This imitation effect can be particularly

[2] To the degree that peers influence financial decision making through the expression or correction of behavioral biases, there is a deep tradition in finance and behavioral economics studying behavioral finance. See Bohren, Hascher, Imas, Ungeheuer, and Weber (2024) for a recent example of frontier research, and Barberis (2013) and Barberis and Thaler (2003) for reviews.

strong in investment settings, where uncertainty and fear of missing out (FOMO) drive individuals to follow the majority.

Recent empirical research highlights the power of celebrity influence and social media in fueling herd behavior. Benetton, Mullins, Niessner, and Toczynski (2024) find that retail investors often follow investment recommendations from celebrities on platforms like Twitter, despite these recommendations yielding negative returns after transaction costs. This underscores the potential downside of herd behavior—while following the crowd can sometimes be rational, it can also lead to misguided investment choices when individuals fail to evaluate risks independently.

1.2.3 The Role of Group Size in Decision-Making. While peer influence is well-documented, the effect of group size on financial decision-making remains an open question. Larger groups may facilitate better decision-making by aggregating diverse perspectives and increasing access to high-quality information. However, they may also introduce coordination challenges and cognitive overload, making it difficult for individuals to extract useful insights.

Jenter et al. (2023) provide a relevant comparison in their study of corporate board size. Their findings indicate that larger boards do not necessarily lead to better firm performance, as communication inefficiencies and conflicting opinions can hinder effective decision-making. Whether this dynamic applies to peer groups in financial decision-making is yet to be determined.

The existing literature establishes that peer effects significantly influence financial decision-making, but the role of group size remains underexplored. This study aims to experimentally test whether larger groups enhance investment decision-making by aggregating information or hinder it by creating noise and inefficiencies. By systematically varying the size of peer groups and measuring investment outcomes, this research will contribute new insights into the optimal structure of peer influence in financial markets.

1.3 Experimental Design

We propose a laboratory study for testing the influence of peer group discussions on financial decision making, and whether that influence depends on group size. The key features of the study are that it will feature two different types of repeated individual financial choices –stated investment preferences, and revealed lottery preferences– with within-subject variation in whether those choices are made individually or in group settings. We first describe the overall structure of the laboratory study, and then elaborate on each of the specific choices, before offering hypothesis and proposed data analysis.

1.3.1 Design Structure. The overall structure of the experiment is illustrated in Figure 1. Each experimental session consists of 16 subjects interacting via computer terminals. First, all participants receive instructions followed by a background knowledge test. The instructions provide a brief overview of essential financial investment skills –including using Yahoo Finance to research assets– describe the upcoming tasks, outline the available information, and explain the payment structure. The background knowledge test will categorize participants into two types –High (H) and Low (L)– based on their knowledge of financial markets. This will be a 10-question battery consisting of questions about calculating compound interest, knowledge of key financial terms (e.g. "call" vs. "put" options), and asset classes (e.g. stocks vs. bonds). During each experimental session, the highest-scoring eight subjects are labeled H and the others are labeled L, with ties broken randomly to maintain two equal groups of eight. We will also include questions about how regularly and recently a participant has consumed financial news (e.g. we will ask participants about the number of times they spent at least 10 minutes reading or watching financial news and other content in the previous week by having them select frequency ranges from a given set of options).

The main data collection portion of the experiment consists of three rounds of investment decisions. In the first round (R0), participants make individual choices based solely on their own knowledge and skills. In the second round (R1), participants are assigned to either a 2-person group (H+L) or a 4-person group (HH+LL). In the third round (R2), the group sizes are switched: the 2-person groups expand to 4-person groups (HH+LL), while the 4-person groups reduce to 2-person groups (H+L). By keeping the session size fixed at 16, groups of unique partners can always be constructed in R2. The elements of each round are described in the next section.

Following R2, participant earnings are calculated and subjects receive their participation payments before leaving. All subjects earn a fixed fee, to be determined at a later date, for participating, and it must be substantial enough to compensate them for their time even in the case that they lose some money during the rounds.

We will implement the study in a college classroom setting, designed to take 90 minutes total. Students will be asked to bring a laptop or smartphone to class in order to participate. Instructions will be provided through the digital survey platform rather than announced by the study leader in order to make the implementation more uniform across different classes. After following a link provided via QR code to the study, students will encounter an informed consent screen, followed by the introduction and instructions. Using a timed advance

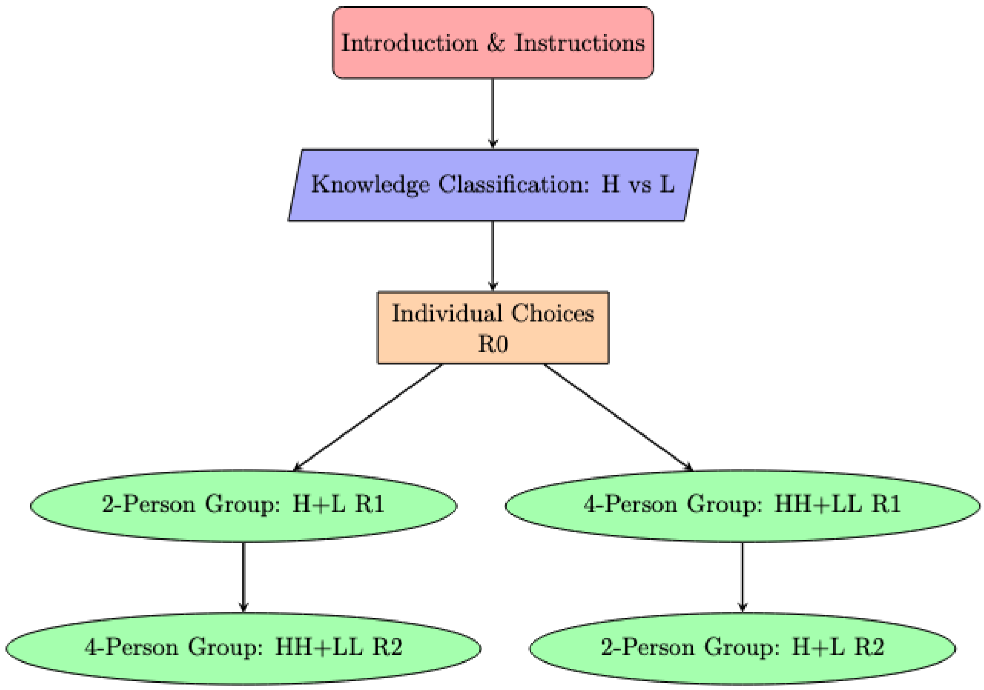


Figure 1. Layout of Study

option, they will be required to spend at least 10 minutes on the instructions. They will proceed directly to the knowledge classification test (with a 5 minute timer) and R0 (with a 20 minute maximum timer and a 15 minute minimum timer before the option to submit responses activates).

Once all students have completed R0 (enforced through the timers), they will be randomized into either the large or small R1 group treatment. These groups, and the subsequent R2 groups will be implemented in person: each group will be assigned an ID number, and students will need to find their partners and sit together for R1 and R2. There will be 20 minute maximum and 15 minute minimum timers in place for R1 and R2 as well, and in this case participants will not be able to finalize their answers until all group members have done so.[3]

Given the fact that the discussions will be in person, personal characteristics could influence the decision-making process. For instance, men and women might engage in different levels of risk taking, and this could result in sex differences in peer effects; participants with finance or economics background might have more expertise (or overconfidence) and propagate specific types of peer effects. Because of this, it is crucial that the treatment randomization be balanced along dimensions that could be relevant for financial behavior and peer effects therein. As part of the financial knowledge survey we will collect gender, race, and major. We will then performed stratified randomization within the eight cells defined by the 2x2x2 interaction of sex, white/non-white race, and economics/finance/business majors vs. others. Assignment to H or L financial knowledge will then be done within each treatment group to enable the successful formation of all groups.

1.3.2 Financial choices. Each choice stage of the study –R0, R1, and R2– consists of two tasks. Task 1 is a realistic stated preference task where subjects engage in a hypothetical portfolio choice task. Task 2 is an abstract portfolio choice task with monetary rewards designed to elicit easy-to-interpret measures of decision quality.

1.3.2.1 Task 1: Stated investment preferences. In Task 1, participant will construct a realistic portfolio among several investment options, such as mutual funds, cash, bonds, stocks, etc. Participants will be asked to imagine they have a portion of their paycheck that they invest in the market each month, and they are deciding how to allocate it across asset classes. A

[3] Specifically, if the first person in a group clicks "submit" once it is available, there will remain an option to go back until the last person in a group clicks submit or the timer expires.

sample question is shown in Figure 2, with options for mutual funds, cash, bonds, cryptocurrency, (individual) stocks, and other assets. The choices are framed as deciding where each dollar from a $100 budget goes for simplicity, but the instructions will clarify that this is representative of whatever the overall investment amount is. For example, a participant could choose to invest $25 in equities, $25 in bonds, $25 in cyrptocurrency and leave the rest $25 as cash saved in the bank. All participants will be instructed to imagine that there is a target date five years in the future that they are investing for.

We will characterize portfolios based on features associated with risk taking. For example, imagine that Individual 1 is highly risk-averse and thus selects $50 in bonds and $50 cash. On the other hand, imagine Individual 2 is more risk tolerant and thus selects $30 in cryptocurrency, $50 in stocks, and $20 in mutual funds. A variable that measures *the share of a portfolio dedicated to cryptocurrency and stocks* would be zero for Individual 1 and 0.8 for Individual 2. Call this variable P_R: a measure of portfolio-level risk-taking. In addition to P_R, we will create a variable equal to the share of a portfolio in safer bonds and cash, called P_S. This would be 1 for Individual 1 and 0 for Individual 2.

Associated with the share of the portfolio that participants dedicated to stocks, we will ask them to list the top five stock ticker symbols (by dollars invested) that they would choose for their portfolio. An example of this elicitation screen is in Figure 3. If they would invest in fewer than five individual stocks, then they are free to list fewer options. We plan to classify these choices based on the volatility of the selected ticker symbols and the number selected. Volatility, V is measured as 52-week range of the stock (upper bound less lower bound) normalized by the current price, and then we will take the average across listed stocks, $\bar{V}$. The

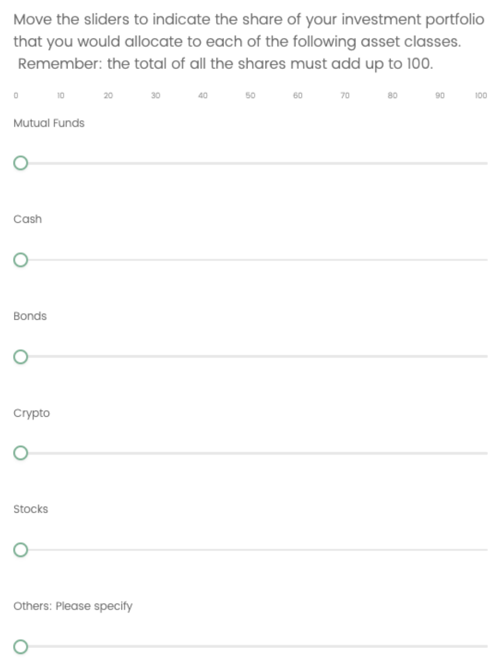
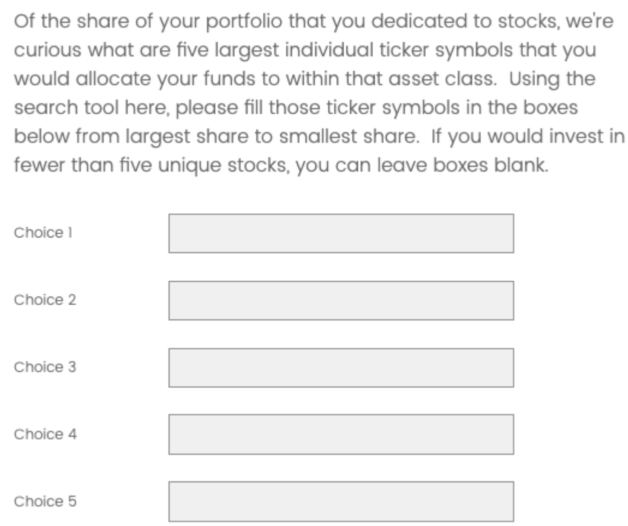


Figure 2. Portfolio Allocation

number of listed stocks, N is used as a measure of diversification, and we will also consider an adjusted volatility measure, $V_A = \frac{\bar{V}}{N}$ that combines the two.



Of the share of your portfolio that you dedicated to stocks, we're curious what are five largest individual ticker symbols that you would allocate your funds to within that asset class. Using the search tool here, please fill those ticker symbols in the boxes below from largest share to smallest share. If you would invest in fewer than five unique stocks, you can leave boxes blank.

Choice 1

Choice 2

Choice 3

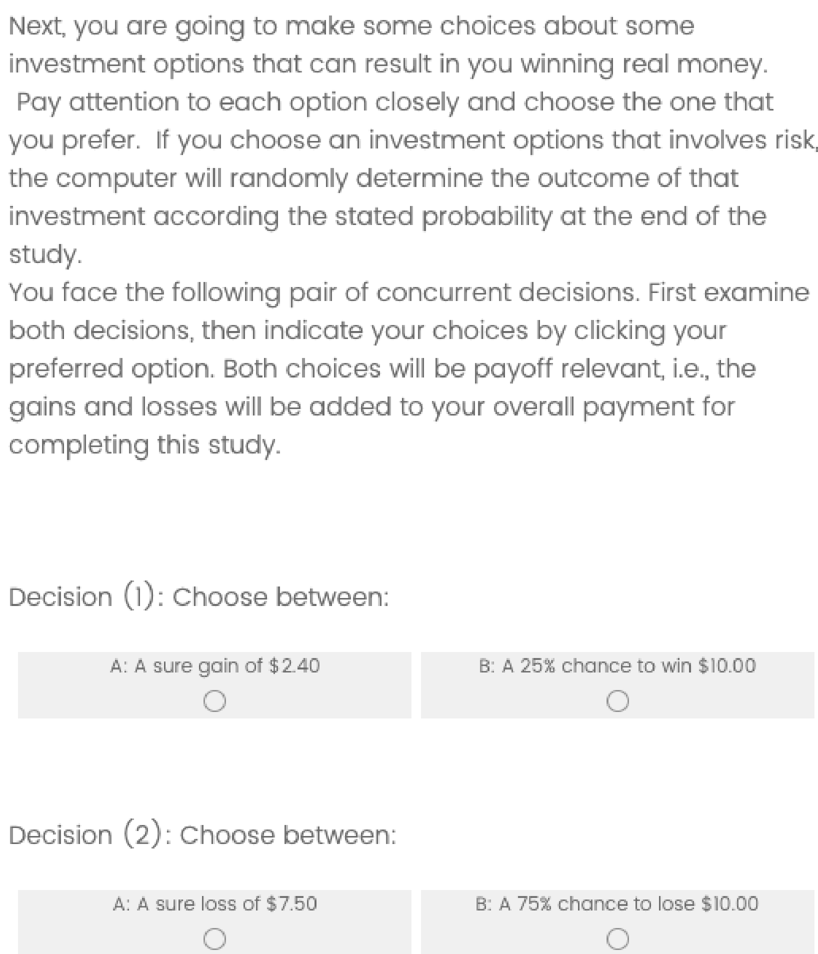
Choice 4

Choice 5

Figure 3. Top 5 Single Stocks

1.3.2.2 Task 2: Revealed lottery preferences. Real money consequences will be implemented in Task 2. We will adopt the portfolio choice tasks of Rabin and Weizsäcker (2009) to allow participants to make investment choices by choosing risky assets with objective probabilities. The key feature of these questions is that they allow subjects to easily make patterns of choices that are first-order stochastically dominated. This allows us to characterize decisions as "errors" by a somewhat objective metric. Consider the example shown in Figure 4; participants make two decisions, with *both* decisions counting. Decision 1 is between Option A: a sure gain of \$2.40 and Option B: a 25% chance to win \$10.00 (with a 75% chance of winning nothing). Decision 2 is between Option A: a sure loss of \$7.50 and Option B: a 75% chance to lose \$10.00 (with a 25% chance of losing nothing).

These two decisions play on the classic Prospect Theory result that individuals often appear more willing to task risks to avoid losses than to secure gains. Specifically, $A \rightarrow B$ is a tempting choice profile under such preferences *when the two decisions are mutually exclusive*. When they are both payoff relevant, this profile creates a payoff of a loss of \$7.60 with probability 0.75 and a gain of \$2.40 with probability 0.25. This profile is dominated by $B \rightarrow A$, which creates a payoff of a loss of \$7.50 with probability 0.75 and a gain of \$2.50 with probability 0.25. We use the variable D to indicate whether an individual makes a set of decisions in Task 2 that are dominated.


Next, you are going to make some choices about some investment options that can result in you winning real money. Pay attention to each option closely and choose the one that you prefer. If you choose an investment options that involves risk, the computer will randomly determine the outcome of that investment according the stated probability at the end of the study.

You face the following pair of concurrent decisions. First examine both decisions, then indicate your choices by clicking your preferred option. Both choices will be payoff relevant, i.e., the gains and losses will be added to your overall payment for completing this study.

Decision (1): Choose between:

A: A sure gain of \$2.40

B: A 25% chance to win \$10.00

Decision (2): Choose between:

A: A sure loss of \$7.50

B: A 75% chance to lose \$10.00

Figure 4. Rabin and Weizsäcker (2009) Example Decisions

Within each iteration of Task 2 (R0, R1, R2), we will use slightly different numbers for the options in each decision, pulling three sets of options and decisions from Rabin and Weizsäcker (2009). The order will be randomized at the subject level across rounds. At the end of the study, we will randomly select one of the three implementations of Task 2, and then realize both Decision 1 and Decision 2 at the subject level. The resulting payoffs will be added or subtracted from their participation fee.

1.3.3 Treatment Variation. After three rounds (R0, R1, R2), difference-in-difference analysis will be used to obtain the treatment effects of peer group size. Our two-stage symmetric randomization exposes all participants to both large and small peer groups, but in varying order. Within this design the most precise identification of the effect of group size is between treatment groups in R1. We can observe exactly how outcomes differ between 2-person groups in R1 and 4-person groups in R1 facing the exact same set of options. We can add precision to this single difference, by differencing out individual performance in R0 and adding individual fixed effects.

Beyond the main analysis of the treatment effect of peer group size in R1, we will measure whether there are symmetric effects of increasing peer group size from R1 to R2 and decreasing peer group size from R1 to R2. We can estimate both of these difference-in-difference effects using the same regression equation. Call Y_{ij} one of our specified outcome variables $(P_R, P_S, V, \bar{V}, V_A, D)$ for participant i in round j, and T_i an indicator variable for whether participant i is assigned to the *four-person group* in R1. We will estimate the following OLS model with participant fixed effects:

$$Y_{ij} = \alpha_i + \beta_1 \mathbb{1}(j > 0) + \beta_2 \mathbb{1}(j > 0) \times T_i + \beta_3 \mathbb{1}(j = 2) \times (1 - T_i) + \beta_4 \mathbb{1}(j = 2) \times T_i + \epsilon_{ij}. \tag{1.1}$$

We plan to cluster standard errors at the R1 group level, and to also consider distributional versions of the tests summarized in this single linear regressions (e.g. Kolmogorov-Smirnov tests applied to the distributions of Y_{ij} in two experimental cells.

In this model, the individual fixed effect, α_i measures the outcome variable in the individual decision-making round, R1. β_1 measures the effect of being placed in a two-person group on the outcome, and β_2 tests whether this effect is any difference for four-person groups. β_3 measures the effect of increasing group size from R1 to R2 and β_4 measures the effect of decreasing group size from R1 to R2. The map from the regression coefficients to treatment-by-round mean outcomes is shown in Table 1.

Table 1. Map from Coefficients to Means

	R0	R1	R2
$T_i = 0$: size 2 in R1, size 4 in R2	α_i	$\alpha_i + \beta_1$	$\alpha_i + \beta_1 + \beta_3$
$T_i = 1$: size 4 in R1, size 2 in R2	α_i	$\alpha_i + \beta_1 + \beta_2$	$\alpha_i + \beta_1 + \beta_2 + \beta_4$

1.3.4 Hypotheses.

The interpretations of β_1 and β_2 potentially depend on one another, and we show this relationship in Table 2.

Table 2. Effects of Group & Size

	β_1			
		-	0	+
β_2	-	size increases effect	only large groups matter	size mitigates effect
	0	groups matter, not size	groups don't matter	groups matter, not size
	+	size mitigates effect	only large groups matter	size amplifies effect

Hypothesis H01: $\beta_1 = 0, \beta_2 = 0$.

Our first null hypothesis is represented by both β_1 and β_2 equaling zero. This would suggest that outcomes are not affected by the switch from individual decision making to decision making under the influence of peers, regardless of group size.

Hypothesis HA1: $\beta_1 \neq 0$.

If, alternatively, $\beta_1 \neq 0$, we have suggestive evidence that even communication with a single peer can influence decision making. However, this single difference is not separately identified from the general effect of repeating a task a second time in R1 after having first encountered it in R2. When $\beta_2 \neq 0$ also, not only is there evidence of an effect of group size mattering for peer effect, but this strengthens the attribution of the β_1 effect to peer influence on decision making. A larger group with more peers might amplify or mitigate the effects of peers depending on whether the amount of information effect or quality of communication effect dominates. If $\beta_1 < 0$ and $\beta_2 < 0$, or $\beta_1 > 0$ and $\beta_2 > 0$, the larger group amplifies the effect of peers; if $\beta_1 < 0$ and $\beta_2 > 0$, or $\beta_1 > 0$ and $\beta_2 < 0$, the larger group mitigates the effect of peers.

Hypothesis HA2: $\beta_1 = 0, \beta_2 \neq 0$.

If $\beta_1 = 0$ but β_2 does not, this is evidence that only groups of a large enough size will lead to peer effects on outcomes.

Hypothesis H02: $\beta_3 = -\beta_4$.

Our second null hypothesis is that the effect of increasing the group size from two to four has a symmetric within-subject effect of decreasing group size from four to two.

Hypothesis HA3: $\beta_3 \neq -\beta_4$.

If, alternatively, these two coefficients are not equal, this means that peer effects are "sticky". This most likely interpretation for this finding would be that decisions in group settings are anchored to the first set of decisions made in a group context. There are other potential interpretations of such findings, that would depend on how β_3 and β_4 relate to β_1 and β_2.

1.4 Implementation Plan

Due to time and financial constraints, we have not yet been able to run the study. However, this proposal represents an off-the-shelf, ready to implement study that can play a role in a future Ph.D. dissertation. It is financially feasible to implement using the classroom data collection strategy. Our goal would be to power this experiment to detect a 10pp change in a discrete outcome with 5% statistical significance –i.e. the rate of dominated choices in the Rabin and Weizsäcker (2009) task– with 80% confidence. This requires a maximum of 392 independent observations per treatment group. Under the very conservative assumption that each R1 group represents only one independent observation, this requires a total of 2,352 subjects randomized into large or small R1 groups at a ratio of 2:1. However, a balanced randomization is easier to implement, and we would thus target a sample of 3136 students randomized at 1:1. We could achieve this sample with 20 200-person classroom studies, assuming an attendance/consent rate of just under 80%. From each class, we would randomly select one individual for a $200 participation fee, from which their Task 2 earnings from R0, R1, or R2 would be randomly applied. The maximum cost of this study would be $6000, which would require either a small grant or faculty research funding.

REFERENCES CITED

Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics*, *107*(3), 797–817.

Barber, B. M., & Odean, T. (2013). The behavior of individual investors. *Handbook of the Economics of Finance*, *2*(B), 1535–1570.

Barberis, N. C. (2013, February). Thirty years of prospect theory in economics: A review and assessment. *Journal of Economic Perspectives*, *27*(1), 173–96. doi: 10.1257/jep.27.1.173

Barberis, N. C., & Thaler, R. (2003). A survey of behavioral finance. In G. Constantinides, M. Harris, & R. Stulz (Eds.), *Handbook of the economics of finance* (1st ed., Vol. 1, pp. 1053–1128). Elsevier.

Benetton, M., Mullins, W., Niessner, M., & Toczynski, J. (2024). *Celebrity persuasion.* (Online Working Paper 2024)

Bohren, J. A., Hascher, J., Imas, A., Ungeheuer, M., & Weber, M. (2024, February). *A cognitive foundation for perceiving uncertainty* (Working Paper No. 32149). National Bureau of Economic Research. doi: 10.3386/w32149

Case, A. C., & Katz, L. F. (1991). *The company you keep: The effects of family and neighborhood on disadvantaged youths.* (NBER working paper 3705)

Ellison, G., & Fudenberg, D. (1995). Word-of-mouth communication and social learning. *The Quarterly Journal of Economics*, *110*(1), 93–125.

Henderson, V., Mieszkowski, P., & Sauvageau, Y. (1978). Peer group effects and educational production functions. *Journal of Public Economics*, *10*(1), 97-106. doi: https://doi.org/10.1016/0047-2727(78)90007-5

Jenter, D., Schmid, T., & Urban, D. (2023). *Does board size matter?* (European Corporate Governance Institute – Finance Working Paper 916/2023)

Katz, L. F., Kling, J. R., & Liebman, J. B. (2001-05). Moving to opportunity in boston: Early results of a randomized mobility experiment. *The Quarterly Journal of Economics*, *116*(2), 607–654.

Ouimet, P., & Tate, G. (2020). Learning from coworkers: Peer effects on individual investment decisions. *The Journal of Finance*, *LXXV*(1), 133–172.

Rabin, M., & Weizsäcker, G. (2009). Narrow bracketing and dominated choices. *American Economic Review*, *99*(4), 1508–1543.

Zimmerman, D. J. (2003). Peer effects in academic outcomes: Evidence from a natural experiment. *The Review of Economics and Statistics*, *85*(1), 9–23.