

Effects of Peer Observation on Risky Decision-Making in Adolescence: A Meta-Analytic Review

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Real-world health and crime statistics indicate that adolescents are prone to engage in risks in the presence of peers. Although this effect has been documented in several lab studies, existing evidence varies and the psychological mechanisms that give rise to peer observation-induced shifts in adolescent risky decision-making remain poorly understood. We conducted a systematic literature review and meta-analysis to quantify the magnitude of the effect of direct peer observation on risky decision-making in adolescents. Across 186 effect sizes, representing data from 53 distinct research reports and over 5,000 participants, we found evidence that during adolescence, observation by peers increases decisions to take risks relative to decisions made while unobserved, with a small mean effect size (Hedges' $g = 0.16$). We also found high effect size heterogeneity ($I^2 = 82.63\%$ and $\tau^2 = 0.078$), motivating analysis of moderation. We evaluated whether variables hypothesized by theory and prior research to amplify or reduce risk taking in the presence of peers systematically moderated the size of this effect, including factors related to the decision context, the peer context, and the experimental design. The overall effect was moderated by peers' expression of risk-seeking preferences, such that the effect of peer observation was only significant when peers were also expressing pro-risk attitudes. Evidence for publication bias was not consistently observed. Taken together, this work supports the notion that mere peer observation increases adolescent risky decision-making, but this effect is extremely small unless the peers are additionally expressing pro-risk preferences. Moreover, this work provokes questions regarding whether the field's approach to studying peer influence is optimal at conceptual and practical levels, and whether it is maximally translatable to real-world contexts. We offer suggestions for future work that could lead to a clearer understanding of peer observation effects during adolescence.

Public Significance Statement

Adolescents are conceptualized as risk-takers in the presence of peers, as evident in real-world health statistics, laws, and policies such as graduated licensing procedures that restrict the number of nonfamily passengers for adolescent drivers. The present meta-analytic review found that peer observation increased adolescents' tendency to make risky decisions, but the effect is small in magnitude and was much greater when peers were expressing pro-risk preferences. We discuss the practical relevance of an effect of this size, provide recommendations to the field for conducting research toward a robust, translatable understanding of the nature of how peers influence preference for risk during adolescence, and discuss implications for policies involving youth decision-making in social contexts.

Keywords: risk taking, decision-making, adolescence, peers, peer influence

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Adolescence, which begins around the onset of physical puberty and ends with the assumption of adult roles, is a dynamic phase of development characterized by physical, neurobiological, and psychological maturation (Blakemore & Mills, 2014; Spear, 2000; Steinberg & Morris, 2001). While this normative transition from childhood to adulthood is marked by cognitive and behavioral achievements, adolescence is also known as a time when the tendency to engage in risky behaviors escalates and contributes to common health risks in this age group (Boyer, 2006; Steinberg, 2008). Although risk-taking behavior should not automatically be conceptualized as negative (as discussed below), a major focus of applied research on youth is on engagement in *health risk behaviors*, which are largely considered to exert adverse impacts on an individual's developmental trajectory. According to the USA-based Center for Disease Control, health risk behaviors include as follows: behaviors that contribute to unintentional injury or violence; tobacco, alcohol, and other drug use; sexual behaviors that contribute to unintended pregnancy and sexually transmitted illness/human immunodeficiency virus infection; unhealthy dietary behaviors; and physical inactivity (Underwood et al., 2020). On one hand, most individuals traverse adolescence without intensive engagement in health risk behaviors. On the other hand, the tendency to engage in health risk behaviors escalates during adolescence, as documented in real-world data on adolescent driving, engagement in substance abuse and unsafe sexual practices, and physical risks that could lead to injuries or death (Eaton et al., 2008; Underwood et al., 2020).

Understanding the phenomenon of adolescent risky behavior is aided by experimental research aimed at characterizing the nature of this collection of behaviors and the conditions that give rise to them. Indeed, substantial research has been conducted on adolescent risk-taking behavior and the individual-level, decision-level, and situational contexts that may increase its incidence. This work informs psychological theory and is consumed by scientists as well as those who guide public policies impacting youth and communities. To translate research findings responsibly requires an accurate, comprehensive characterization of risky behaviors and the conditions that may increase their odds of occurrence. The present report offers a systematic analysis of experimental research evaluating peer observation as a context that is thought to exacerbate adolescent risk taking. Here, we evaluate the strength of this effect using robust meta-analytic methods and explore moderators that may increase or decrease the odds that peer observation makes adolescents' decisions more risky.

Adolescent Risk Taking and the "Peer Effect"

Public health data indicate that certain situational variables increase the likelihood that adolescents will engage in health risk behaviors. One such context is when adolescents are in the presence of their peers. For example, analyses of car accident data have revealed that accident rates for adolescent drivers increase considerably when passengers are present, relative to when adolescents drive alone and relative to when young adults drive with passengers in the car (Aldridge et al., 1999; Chen et al., 2000; Doherty et al., 1998). Moreover, adolescents' accident rates are further elevated when multiple passengers are present in the car (Doherty et al., 1998). The fact that peer passengers are associated with adolescent driving accidents and deaths propelled widespread policy changes in the United States including education programs and graduated

licensing laws aimed at controlling the social climate inside vehicles operated by adolescent drivers (Beck et al., 2002). In addition to driving, peers have been implicated in adolescent decisions to take risks in other domains, such as drinking and using illegal substances (Chassin et al., 2009; Kandel, 1985), underscoring the importance of understanding how peer contexts intersect with risk taking during adolescence.

Although the public health data demonstrate the impact of peers on adolescent risky decisions, the root mechanisms of this "peer effect" remain unclear. Both nonpsychological and psychology-based explanations have been put forth to account for this phenomenon. Nonpsychological explanations focus on factors such as convenience and availability of risky situations. That is, adolescents could engage in more risky choices around peers because parental oversight is less likely during interactions with peers, and adolescents are more likely to have access to risk-enabling situations when with peers than when alone (Osgood & Anderson, 2004). On the other hand, psychology-based explanations highlight the unique developmental milieu of adolescence as a period of life when peers could provoke motivations or transmit norms differently than other phases of development. Several related, yet distinct, mechanisms have been proposed to account for adolescents' tendency to take greater risks with peers. As described in detail below, adolescents could take risks in the presence of peers to preserve or elevate their own social status (Brechwald & Prinstein, 2011; Cohen & Prinstein, 2006), in a bid to increase social acceptance (Engels & Ter Bogt, 2001; van den Broek et al., 2016), because of an overestimation of peers' acceptance of risk (Prinstein & Wang, 2005), or because reward processing is escalated when peers are involved in a risk-taking context (Albert et al., 2013; Chein et al., 2011).

Over the past decade, a wave of experimental psychology research has been conducted to evaluate the psychology-based explanations for the outsize effect of peers on adolescents' risky decision-making. These controlled laboratory studies that manipulate and measure adolescent decision-making when experiencing (vs. not) the concurrent observation of peers, aim to isolate whether and why peers impact decisions around risk. Though many experimental studies have amassed, the field lacks a precise estimate of the size and reliability of the effect of peers on adolescent risky decisions. To fill this gap in understanding, we conducted a meta-analysis synthesizing a broad range of experimental studies to quantify the magnitude of the effect of direct peer observation on adolescent risk-taking relative to decisions made alone.

We also evaluated whether this effect size was systematically moderated by several theoretically relevant variables that have been proposed to influence the strength or direction of the effect of peer observation on risky decision-making. These moderators include aspects of the risky decision context (e.g., the presence of immediate outcome feedback; availability of a nonrisky choice option; level of arousal or excitement inherent to the experimental context) and aspects of the peer context (e.g., number of peers present; whether peers are personally known or unfamiliar to the participant; whether the peers are actively expressing pro-risk preferences). Answering these questions by analyzing the large body of available data can offer theoretical insights about the psychological factors influencing adolescent decision-making and holds the potential to inform the contexts in which adolescents may be especially vulnerable to health risks.

Risky Decision-Making in Adolescence

Definitions and Assessments

Lay and nonspecialist conceptions of *risk* frequently assume that a “risky” decision is one that yields unhealthy or adverse consequences. Within this definitional framework—where risky decisions should be avoided, and public health policies should aim to curb the frequency and intensity of risky choices—adolescents have been labeled as poor decision makers whose decision processes lead them to engage in risks that threaten their health. Yet, this account of risk can conflict with accounts from the fields of decision science and economics, which define a “risky” decision as one that has a greater variance in possible outcomes (i.e., *outcome variability*; Figner & Weber, 2011; Weber et al., 2004). For example, given a choice between two lotteries, one paying out \$0 or \$10 with 50% probability of each, and another paying out \$3 or \$7 with 50% odds of each, the expected value is equivalent, but the first lottery is considered riskier because the variance of possible outcomes is larger. This definition can also be applied to real-world decisions: Choosing to try an illegal drug is riskier than choosing not to try it under the same logic, as there is greater variability in the possible outcomes associated with trying the drug (e.g., enjoyment, acute illness, overdose, arrest) compared to abstaining.

In the present meta-analysis, we adopt *outcome variability* as the definition of risk, with behaviors that select the more variable option as the operational definition of a “risky” decision. We then apply this definition to a wide range of tasks in the literature. It is important to note that under this framework, risky decisions are not necessarily suboptimal. Rather, choosing to take a risk is thought to result from a host of interactive processes that can be shaped by development (Reyna & Farley, 2006). Indeed, in real-world settings, engaging in risky choices can be advantageous, or advantageous up to a point. For instance, deciding to audition for a lead part in a school play is inherently riskier than deciding not to, though many would agree that the risk could lead to constructive outcomes (e.g., learning to cope with failure) even if the negative outcome transpired (e.g., not getting the part). Choosing risk may have especially complex potential outcomes during adolescence, when individuals are immersed in intensive learning about the world through their own experiences (Blakemore & Mills, 2014; Crone & Dahl, 2012). Thus, it is important to draw a distinction between *risky decisions*, the focus of examination here, and *engagement in health risk behaviors*, such as dangerous driving and substance abuse, that are assumed to be suboptimal and which society broadly aims to minimize.

Operationalization

In the laboratory, risky decision-making has been studied using two primary approaches. One approach, rooted in the judgment and decision-making literature, characterizes a risky choice as the option with the widest range of outcomes, where probabilities of potential outcomes are known or can be estimated based on available information or prior experience (Figner & Weber, 2011; Weber, 2010). In these tasks, participants are typically presented with options that vary in monetary outcomes based on the quantity of gains and losses, the probability of different outcomes, and the outcome variability. Usually, participants are offered choices between two options: a riskier option, where the probability of the outcome occurring is uncertain, and either a less risky option or a “safe” option (that carries no risk,

because the outcome is known with 100% certainty). These tasks can present risks straightforwardly, such as presenting two pie charts depicting the monetary amounts and probabilities associated with each outcome, or using a more elaborate setup, such as the Balloon Analogue Risk Task (BART; Lejuez et al., 2003) in which participants pump to inflate an animated balloon, with each pump updating the tradeoff between greater monetary reward and a greater chance of the balloon exploding.¹ In these tasks—assuming a risk-neutral decision maker—the riskier choice and the mathematically optimal choice can be decoupled so that risk preferences can be isolated from other decision parameters, such as expected value. An advantage of this approach is that researchers are afforded the opportunity to specifically estimate risk preferences.

A second approach incorporates more ecological contexts to assess risky decision-making in the lab using experimental setups constructed to mimic real-world decision contexts. These designs range from computerized driving-games to realistic driving simulators, where risky choices are operationalized in terms of driving behaviors such as speeding, driving through a yellow light, or crashing the car. The more applied nature of these paradigms is intended to capture the complex situations and emotional influences that affect decisions to engage in health risk behaviors in the real world (Gardner & Steinberg, 2005). Importantly, behaviors measured in these ecological tasks also conform to the economic definition of risky decisions, as driving through a yellow light holds greater inherent outcome variability than stopping. Nonetheless, choices in these ecological tasks lack full descriptions of risk, leaving the decision maker to infer the costs and benefits of positive and negative outcomes and their associated probabilities.

Following a previous meta-analysis on adolescent risk taking (Defoe et al., 2015), we focused on synthesizing results from both “economic” and “ecological” experimental decision-making tasks to capture a broad range of basic decision-making processes under risk. Moreover, comparing the effect sizes for these studies may reveal boundary conditions of laboratory-evoked peer observation effects. Though not included in the present meta-analysis (following Defoe et al., 2015), self-report questionnaires are also commonly used in research to assess risk preferences and engagement in health risk behaviors. Many researchers use questionnaires in conjunction with experimental methods, given the challenges associated with relying on self-report methodologies and responses to hypothetical scenarios (e.g., response bias). For more detailed descriptions of this methodological approach, we point interested readers to Charness et al. (2013) and Dohmen et al. (2011).

Age-Related Patterns

While statistics on public health risks suggest that adolescents engage in risky behavior more frequently than adults, the experimental evidence has been mixed. Several studies concluded that the tendency to make risky decisions is elevated during the mid-adolescent years

¹ In the literature, a distinction is sometimes made between decisions involving choices that have completely known and partially or completely unknown probabilities. In these cases, the former is called *risk* in the narrow sense, and the latter is called *ambiguity* (Knight, 1921). For the purposes of this project, we include both nonambiguous and ambiguous decisions in the meta-analysis so long as the decisions meet our definition of *risk*. Analyses test a moderator variable representing ambiguity that compares effect sizes for which probabilities were known or unknown to the participant.

relative to older and/or younger individuals (Burnett et al., 2010; Cauffman et al., 2010; Figner et al., 2009). Still, other work has revealed a pattern where decisions to take risks peak in childhood and then decline linearly throughout adolescence into adulthood (e.g., Paulsen et al., 2012), and still other work has shown no evidence of changes across development (e.g., Van Leijenhorst et al., 2008).

In an effort to resolve some of these inconsistencies, Defoe et al. (2015) conducted a meta-analysis on adolescent risk taking that synthesized results across a variety of experimental risky decision tasks and age groups (children, adolescents, adults). Analyses revealed that adolescents make riskier decisions than adults—a medium-sized mean effect—and that children and adolescents exhibit an equivalent tendency to make risky decisions. Targeted moderator analyses revealed that tasks that provide participants with immediate feedback regarding wins and losses led to the greatest increases in risky choices in adolescents relative to adults. Thus, much like trends in public health statistics, results from laboratory studies generally converge on the conclusion that there is a greater orientation towards risk in decisions during the adolescent years compared to adulthood (but not compared to childhood) and that important moderating factors exist. Through the present meta-analysis, we aim to quantify how the situational factor of *peer observation* shapes adolescents' tendency to make risky decisions, a claim that has already shaped policy and holds implications for understanding the health risk challenges adolescents face in the real world.

Peers and Peer Observation

Definitions and Assessments

A key feature of adolescent life is immense social change. Adolescents spend more time with their peers and less time with their parents (Barnes et al., 2007; Larson, 2001), become increasingly attuned to signals of social rejection and acceptance from peers (Guyer et al., 2012; Rodman et al., 2017; Silk et al., 2012; Somerville, 2013), and shift towards other-focused, prosocial behaviors (Crone & Dahl, 2012). This “social reorientation” leads to a complex social landscape populated by dynamically changing peer groups, shifting alliances, and salient social hierarchies (Brown, 2004).

Peers have been implicated in many accounts of increased engagement in health risk behaviors during adolescence. These accounts draw on real-world crime and health statistics that reveal that adolescents are more likely to commit crimes (Zimring, 1998), use illegal substances (Chassin et al., 2009), and drive recklessly (Williams et al., 2007) when peers are present. To examine whether peers increase the tendency to make risky decisions during adolescence, researchers have devised clever ways to introduce peers into the experimental decision-making contexts described above. Because access to risk can be held constant across conditions with and without peers in controlled laboratory studies, adolescent risk taking during peer observation cannot be attributed merely to adolescents' greater access to risk-taking opportunities when they are with peers (Osgood & Anderson, 2004).

During risky decision-making tasks, researchers have manipulated whether peers are physically present during the decision-making task or virtually present and observing decisions remotely (i.e., via a camera or internet chatroom); whether peers are friends, classmates, or strangers; whether one peer or multiple peers are

observing; and whether peers interact with the participant and overtly try to influence decisions to take risks.

Theoretical Explanations

Research from *developmental psychology* suggests that decisions to take risks may be shaped by the particular social motivations of adolescents. Several interrelated theoretical perspectives have been put forth to explain how and why active observation by peers may have an outside influence on adolescents' decisions. These perspectives can broadly be organized into four proposed mechanisms that are not mutually exclusive: (a) status-seeking, (b) homophily, (c) elevated reward- and emotion-related processes, and (d) impaired cognitive processing. Each of these four potential mechanisms are discussed in turn.

Peer observation may drive up adolescent risk taking through a desire for heightened social acceptance or status, paired with a belief that engaging in risky behavior will increase social status. As adolescents orient towards their social worlds and relationships with peers take on heightened importance (Brown, 2004; Nelson et al., 2005), increased risk taking may emerge out of a desire to impress peers, build or maintain friendships, or increase reputational status. Generally, risky behaviors are associated with high status and popularity during adolescence (Juvonen & Ho, 2008; Mayeux et al., 2008; Prinstein et al., 2003; Rose et al., 2004) and thus, engaging in risky behavior under peer observation may function as (or at least, adolescents may believe that it is) a viable route toward raising one's own social status. Likewise, peer approval itself could function as a key social reward that would motivate behaviors judged to increase its attainment (Jones et al., 2014; Telzer et al., 2021).

A related but distinct form of social motivation that adolescents express is a desire to behave similarly to peers (*homophily*; Brechwald & Prinstein, 2011; Kandel, 1978), which in some contexts would lead to heightened risky behavior under peer observation. The motivation to achieve homophily is thought to be especially strong during adolescence and has been documented for behaviors that are associated with perceptions of high social status in this age range, including sexual activity (Prinstein et al., 2003) and smoking (Allen et al., 2005). Finally, homophily also manifests in negative moods and expression of depressive behaviors in a phenomenon known as *corumination*, in which one adolescent's depressive thoughts and attitudes transmit to their peers through extensive dialog and mutually disclosed feelings (Prinstein, 2007; Stevens & Prinstein, 2005).

Adolescents' desire to attain homophily is especially strong toward those peers who occupy positions of high social status (Brechwald & Prinstein, 2011). Research has also found that adolescents place greater reliance on the perceived risk attitudes of peers when making decisions about risky behaviors, and thus adolescents may be more inclined to make risky choices around peers who are risky themselves or who are presumed to value risky choices (Knoll et al., 2015; Mason et al., 2014; Prentice & Miller, 1993), even if those assumptions are inaccurate (Powers et al., 2018; Prinstein & Wang, 2005). These first two mechanisms (social approval and homophily) imply direct, intentional modification of behavior when peers are present and directly observing an individual's decisions.

Other potential mechanisms emphasize how risky behavior could escalate through an impact of peers on basic socioemotional

processes, that could accordingly alter risky choice behavior. One such explanation proposes that increased riskiness under peer observation arises from how peer contexts modulate reward processing. According to this perspective (see Albert et al., 2013), the neural responses that signal potential rewards in the environment are amplified in peer contexts and would propel adolescents to approach rewards and commit risky acts. This viewpoint is supported by empirical work demonstrating that adolescents, but not adults, show greater reward-related activation in the orbitofrontal cortex and ventral striatum (key regions in the brain's reward circuitry) during a risky driving task when being observed by two peers relative to completing the same task alone (Chein et al., 2011). Notably, this effect has not been replicated in similarly designed functional magnetic resonance imaging tasks (e.g., Hinnant et al., 2019). In addition to a focus on reward processing, other researchers have advanced similar logic but emphasized the impact peers could have on physiological arousal or affective state mechanisms. Indeed, prior work has shown that bouts of peer observation are associated with heightened arousal, as measured by peripheral physiology (i.e., skin conductance) and self-reported affect (Somerville et al., 2013). A heightened state of arousal or emotional intensity elicited by peers could, in turn, amplify risky behavior.

A final mechanism presumes that adolescents are susceptible to risky choices under peer observation because peers divert cognitive resources away from the risky choice at hand. For example, in driving contexts, peer passengers are associated with altered gaze patterns thought to indicate limited cognitive capacity available for driving (Pradhan et al., 2014). Distraction could result in less reasoned choice behavior and could manifest as more noisy or variable choices or a greater likelihood of selecting (what is perceived as) the "default" behavior. Peer observation has been associated with more impetuous and more inconsistent choices in economic decision contexts and could arise from lessened cognitive resources devoted to the cost-benefit decision at hand (Tymula, 2019). Whether distraction would lead to riskier choices more often than other patterns remains poorly understood. In certain decision contexts, noisier or more "default" choices could orient toward risks, but that may not be the case in all decision contexts. Thus, in addition to or instead of mechanisms associated with deliberate intent, active social contexts alter reward and/or cognitive processes during adolescence, and in turn, contribute to decisions alter risky choices.

Meta-Analysis

Early empirical investigations that incorporated peers into risky decision-making contexts in the lab have been foundational in forming theoretical accounts of adolescent behavior and shaping the direction of this research area. In the first study to manipulate peer contexts, Gardner and Steinberg (2005) showed that adolescents took more risks in a simulated computer driving task when observed by two same-aged peers than when seated alone. In the decade and a half since, a corpus of work has amassed using wide-ranging approaches to measure the intersection of peers and risky decisions. While several studies have replicated the finding that peer observation increases adolescents' decisions to take risks (Smith et al., 2015; van Hoorn et al., 2017), other studies have only found observable differences between risky choices made in the presence of peers and risky choices made alone within very specific

experimental conditions (Reynolds et al., 2014; Somerville et al., 2019), and still other studies have failed to find reliable peer-driven effects in adolescents (e.g., Hinnant et al., 2019; Powers et al., 2018). The considerable quantity of research conducted to date coupled with the methodological variability in these studies provides a fruitful foundation upon which to quantitatively synthesize results and test for moderating factors that reliably shift the impact of peers on decisions to take risks.

The present meta-analysis had two aims. First, we aimed to quantify the magnitude of the effect of peer observation on adolescent risky decisions. Second, in addition to obtaining an overall estimate of the mean size of this effect, we investigated key moderators that may amplify, reduce, or reverse the effect of peer observation, with the goal of identifying principles that may explain the variation in results across the diverse body of existing research. Each potential moderator is described in detail below. Broadly, moderators are situated within four categories: characteristics of the publication (e.g., publication year); characteristics of the sample (e.g., gender composition); characteristics of the risky decision-making task/measurement; and characteristics of the peer context.

Method

Transparency and Openness

This article meets Level 2 standards defined by the Transparency and Openness Promotion Guidelines. Study methods and reported analyses were preregistered before being conducted. The few analyses conducted that fell outside of the preregistered analysis plan are noted as such. The study preregistration, preregistration addendum, meta-analytic data file, analysis scripts, correspondence templates, and other materials used to conduct this project are available in the Supplemental Materials and through the Open Science Framework (<https://osf.io/bzth6>).

Literature Search

We employed multiple search strategies to identify experimental work for potential inclusion in the meta-analysis. Here, we refer to article-level research products as *reports* and individual data sets as *studies*, with some reports including more than one study. Our literature searches identified reports for inclusion screening, and each study within the reports was screened for inclusion separately.

First, we searched electronic databases using the search engines APA PsycINFO, Web of Science,² PubMed, and Google Scholar using combinations of keywords related to risk (*risk*, *risky*, *risky choice*, *risk taking*, *risky behavior*, *decision-making*), adolescence (*adolescence*, *adolescent*, *development*, *teenagers*, *teens*, *youth*, *young adults*), and peers (*peer*, *social*, *peer influence*, *peer effects*,

² Databases searched: Arts & Humanities Citation Index, Book Citation Index—Science, Book Citation Index—Social Sciences & Humanities, Conference Proceedings Citation Index, Conference Proceedings Citation Index—Social Science & Humanities, Current Chemical Reactions, Emerging Sources Citation Index, Index Chemicus (IC)—1993–present, Science Citation Index Expanded, Social Sciences Citation Index, BIOSIS Citation Index, BIOSIS Previews, CABI: CAB Abstracts, Current Contents Connect, Data Citation Index, Derwent Innovations Index, KCI—Korean Journal Database, MEDLINE (1950–present), Russian Science Citation Index, SciELO Citation Index, Zoological Record.

friends). Additional searches were conducted using the names of prominent researchers in the field of adolescent decision-making, as well as keywords related to adolescence and peers in combination with the names of prominent risky decision-making tasks (*Iowa Gambling Task*, *Cambridge Gambling Task*, *BART*, *Wheel of Fortune*, *Stoplight Driving Task*, *Columbia Card Task*). We also screened the reference lists of articles reviewing the literature on peer influence on adolescent decision-making (Albert et al., 2013; Chein, 2015; Defoe et al., 2019; Steinberg, 2008; van Hoorn et al., 2016). See Supplemental Materials for the syntax of all searches conducted.

Finally, in an effort to protect against publication bias, requests for unpublished or in-progress work were sent to email lists and online discussion boards of relevant societies (*Social and Affective Neuroscience Society*, *Society for Research in Child Development*, *Society for Research on Adolescence*, *Judgment and Decision-Making*) and to several adolescent decision-making researchers directly via email. This step was successful in identifying several reports that were unpublished at the time of the search. The results reported here synthesize findings from published and unpublished research reports available through July 2020.

Inclusion Criteria

The following criteria were used to determine inclusion in the meta-analysis:

Studies Included a Sample of Adolescent Participants

Based on the definition provided by the World Health Organization (World Health Organization, n.d.), adolescence was defined as 10.00–19.99 years of age and studies were included if the minimum and maximum ages of the sample fell within this range (i.e., every participant was an adolescent). When conducting the literature search, we noted that in practice, the term adolescence is used more broadly to refer to samples with ages extending into the early 20s (commonly termed “late adolescence” or “youth” in this literature, though many other studies of this age range would describe them as “adults”).

In an effort to be maximally inclusive of the literature as a whole, we set a second, less stringent level of this criteria and also included studies if the sample’s mean age fell within 10.00–19.99 years (as in Liu et al., 2017). Primary analyses were conducted using the less stringent, “wide” age criterion (mean) and whenever results using the more stringent, “narrow” age criterion (minimum/maximum) deviate, it is reported in the Results section.

Studies Contained an Experimental Decision-Making Task That Measured Risky Decision-Making

Studies were required to include a task that measured risky decision-making as a dependent variable/outcome measure, operationalized as choosing an available option with higher outcome variability than another option (Figner & Weber, 2011; Weber, 2010). Tasks were required to involve actively making choices; studies that involved self-reporting on risk-taking preferences or that asked participants to speculate about hypothetical risky situations were excluded, following distinctions made in prior work (see Gardner & Steinberg, 2005).

Studies Contained an Experimental Manipulation of Peer Observation During the Task

Studies were required to include at least one “observed” condition, in which at least one peer observed the participant’s decisions during the task, and at least one “unobserved” condition in which the participant’s decisions were not visible to peers. Observed conditions included manipulations in which peers were physically present in the same room and watching the participants’ choices, as well as manipulations in which participants were led to believe that peers were remotely or virtually present and observing their choices. Occasionally, studies contained two versions of “unobserved” conditions, one in which the participant was in a room completely alone and one in which peers were merely present in the room with the participant, but not observing choices. Previous work evaluated whether the mere presence of peers was sufficient to increase adolescent risky decision-making, and results did not show support for this idea (e.g., Somerville et al., 2019). Thus, in cases with more than two peer conditions, we chose the available control condition with the least observation (ideally, entirely alone) for analysis and omitted intermediate/hybrid conditions.

Peers were defined as contemporaries of approximately the same age as participants. In the literature, the numerical age of the peers is not often provided, with authors instead using descriptive terms to describe the ages of peers relative to participants, such as “peer,” “classmate,” and “same-age.” We excluded studies that specified large age differences between the participants and peers (e.g., if an adult was present in the peer group) and studies where the participants’ decisions were solely observed by a person who was not a peer (e.g., parent, adult, experimenter).

Studies Contained (or Authors Provided) Sufficient Statistics to Calculate the Effect Size for the Difference in Risk Taking Between Observed and Unobserved Conditions Studies Contained a Nonclinical Participant Sample

If studies contained special clinical populations (i.e., participants with diagnosed clinical disorders), they were eligible for inclusion if results from a healthy control sample were available. In such cases, only results from the healthy control sample were included.

Studies Were Written in English

Coding of Moderators. Studies were assessed independently for each comparison of interest³ by two of the authors to evaluate suitability for inclusion and to code study information and moderators. Interrater agreement between coders was high [interrater reliability (study level) $Mdn = 0.96$; minimum observed = 0.75] and all discrepancies were discussed and resolved to 100% agreement. One additional coder not otherwise involved in the meta-analysis was specifically recruited to code one item for each study—the subjective rating of excitement associated with completing the

³ The term “comparison” denotes each effect size available for inclusion in the meta-analysis. Some studies include more than comparison that meets inclusion criteria for the meta-analysis. Within a study, the sample, experimental conditions, and/or dependent measure may vary across comparisons.

task—to obtain an independent assessment of this item based on the task description alone.

Note that for some studies and some comparisons, a given moderator was not relevant to the design and/or not possible to code. In these cases, they were coded as “not specified” and omitted from the analysis of that specific moderator. The following information was coded for each comparison:

Characteristics Related to Publication

Publication Status (Qualitative: Published, Unpublished). We coded studies as *published*, referring to publication in peer-reviewed journals, or *unpublished*, which encompassed all other studies including theses, dissertations, conference proceedings, in-preparation articles, and otherwise unpublished data sets. This moderator was included to test for publication bias in which published studies would contain larger effect sizes than unpublished studies.

Year (Quantitative: Ranging From 2005 to 2020). We recorded the year of publication for published articles and the year of retrieval for unpublished work. This moderator was included to evaluate whether smaller effect sizes were present in more recent studies that may be held to higher evidentiary standards than older studies.

Characteristics Related to the Sample

Sample Size (Quantitative: Ranging From 13 to 452). We recorded the sample size of usable participants. This moderator was included to evaluate whether smaller and larger sample sizes were associated with larger or smaller effect sizes.

Gender Composition (Quantitative: Ranging From 0 to 100 Percent Female). We calculated the percentage of female participants based on reported demographics of the full sample of participants. If participants were excluded and the demographics of the remaining, usable sample were reported, these values were used. Most studies described participants using binary terms of male or female and did not specify whether participants reported on their sex or their gender. We use the term *gender* to describe participants but acknowledge the inherent limitations with this approach in characterizing individuals' gender identities.

Some prior work has suggested that adolescent males have a higher propensity for risk taking in the presence of peers (Defoe et al., 2020; McCoy et al., 2019) and may be more influenced by social pressure to take physical risks, particularly those related to driving norms (Conner et al., 2003; Shepherd et al., 2011). Conversely, research examining predictors of substance use (cigaretts, marijuana) have found that females are more influenced by their peers' attitudes than males (Mason et al., 2014). Thus, this moderator was included to evaluate whether male or female adolescents were more susceptible to risky decisions under peer observation.

Mean Age (Quantitative: Ranging From 10.9 to 19.9 Years). We recorded the mean age of the full sample of participants. If participants were excluded and the mean age of the remaining, usable sample was reported, these values were recorded. If no information about the mean age of the sample was provided, we used other information as available [e.g., the median age of the sample, or the midpoint of the full age range (i.e., 15, if the age range spanned 14–16 years)]. This moderator was included to evaluate whether a particular phase of adolescence was associated with larger

effect sizes relative to other phases. Based on theoretical accounts of adolescent development (see e.g., Somerville et al., 2013), we specifically tested for two theoretical age-related patterns: linear (increasing or decreasing with age) and quadratic (peaking in mid-adolescence).

Characteristics Related to the Risky Decision-Making Task

Task Approach (Qualitative: Economics-Static vs. Economics-Dynamic vs. Driving-Simulation vs. Driving-Game). We distinguished between four different task approaches that reflect the common ways the field assesses risky decision-making in adolescent populations. The “economic” judgment and decision-making category of tasks is characterized by participants selecting between choice options that are otherwise arbitrary (e.g., simulated lotteries) and in which choice options vary in risk. Within this group of tasks, we coded this variable with two categories: *economics-static*, defined as tasks that involved a sequence of single-shot choices (e.g., Wheel of Fortune Task); and *economics-dynamic*, defined as tasks that involved evolving choice environments with contingent choices (e.g., BART).

Another set of tasks adopts a more naturalistic approach to assessing risky decision-making by more closely mimicking real-world decision contexts, such as driving. Within these tasks, we coded this variable with two categories: *driving-simulation*, defined as tasks that are characterized by realistic driving visuals such as stoplights and passing other cars on the road and often involved completing the task inside of an automobile shell; and *driving-games*, defined as cartoonized tasks that are characterized by a sequence of independent choices of whether or not to brake when approaching a changing traffic signal on the screen (e.g., Stoplight or Yellow Light Task), with each choice yielding a potential gain or loss with a specific probability (not necessarily described to the participant). All driving-simulation studies included in the present meta-analysis only included participants who were of driving age according to local laws. This moderator was included to evaluate whether these differential task approaches yielded different effect sizes.

Whether Task Performance was Incentive-Compatible (Qualitative: Concrete Outcome Available, No Concrete Outcome Available). We determined whether participants believed that a concrete outcome (e.g., bonus money, prize) was available, contingent on their task performance, and coded this variable with two categories: *concrete outcome available* and *no concrete outcome available*. This moderator was included to evaluate whether real-life consequences of decisions influenced effect sizes.

Optimal Task Strategy (Qualitative: More Risky Decisions, More Safe Decisions, More Risky Decisions up to a Point, Risky, and Safe Decisions Equally Optimal). When possible, calculating the expected value of each option across a task allows for the assessment of what types of decisions would be optimal in each task from the perspective of maximizing expected outcomes (e.g., points, money). We compared the computed expected value of the risky options to the computed expected value of the safe options and coded this variable with four categories: *more risky decisions*, indicating that the expected value of the risky options exceeded the expected value of the safe options; *more safe decisions*, indicating that the expected value of the safe options exceeded the expected

value of the risky options; *more risky decisions up to a point*, indicating that taking some risks was more advantageous than taking none or too many (e.g., BART; Lejuez et al., 2003); and *risky and safe decisions are equally optimal*, indicating that the expected value of the safe options was identical to the expected value of the risky options. Certain tasks, including driving simulations where participants were instructed to drive as they normally would, could not be classified into one of these categories. This moderator was included to evaluate whether effect sizes were influenced by whether risky choices were probabilistically advantageous within a specific decision context.

Whether Choice Probabilities were Known or Unknown (Qualitative: Probabilities Known, Probabilities Unknown). We coded whether participants decided between choice options with fully defined outcome probabilities or whether information on outcome probabilities was incomplete or not fully defined and coded this variable with two categories: *probabilities known* and *probabilities unknown*. This distinction is often used to differentiate between risky choices (probabilities are known) and ambiguous choices (probabilities are partly or completely unknown; Knight, 1921).

Prior experimental work has disentangled the contributions of attitudes about risk and ambiguity towards choice behavior to reveal that adolescents have a higher tolerance for the unknown than adults (Tymula et al., 2012). Thus, peers might impact attitudes about risk and ambiguity in different ways (Blankenstein et al., 2021; Braams et al., 2021; Tymula, 2019). This moderator was included to evaluate whether the influence of peer observation would be more prominent when the odds of positive and negative outcomes of risk were or were not clearly specified.

Whether Immediate Performance Feedback was Provided (Qualitative: Immediate Feedback Provided, No Immediate Feedback Provided). We identified whether or not participants were provided with immediate feedback about the outcome of their choice and coded this variable with two categories: *immediate feedback provided* and *no immediate feedback provided*. This moderator was included to evaluate whether receiving immediate feedback revealing positive or negative outcomes of choices led to greater effect sizes (Defoe et al., 2015).

Whether a Safe Option was Available (Qualitative: Safe Option Available, Safe Option Unavailable). We identified whether tasks contained a choice option associated with complete certainty (i.e., zero risk) and coded this variable with two categories: *safe option available*, if a choice is present that does not contain outcome variability; and *safe option unavailable*, if all options held some degree of outcome variability. This moderator was included to evaluate whether decision contexts presenting two differentially risky options yielded different effect sizes than decision contexts in which the option of a safe choice was available.

Subjective Rating of Excitement (Quantitative: Ranging 1–7). An independent coder assessed the amount of excitement associated with the subjective experience of completing each task. Excitement was rated on a scale ranging from 1 (*not at all exciting*) to 7 (*very exciting*) based on the task description. This moderator was included to evaluate whether more exciting tasks were associated with greater effect sizes. Prior theory and research indicates that adolescent risk taking most often occurs in emotionally arousing or “hot” contexts (Figner et al., 2009) and the presence of peers in the decision context may further elevate this tendency.

Characteristics Related to the Peers and Peer Context

Type of Unobserved Condition (Qualitative: Alone, Group Testing). We identified the description of the conditions comprising the peer manipulation and coded this variable with two categories: *alone*, if the unobserved condition involved testing participants alone in a room by themselves, and *group testing*, if the unobserved condition involved simultaneously testing multiple participants, who could not directly observe the choices of fellow participants, in a room together. This moderator was included to evaluate the qualities of the “group testing” context, a common configuration in experiments investigating effects of peer observation.

Previous work has suggested that the mere presence of peers in the same room (but without direct observation of choices) is not sufficient to evoke increased risk taking among adolescents (Somerville et al., 2019). Thus, this moderator was included to evaluate whether *alone* and *group testing* contexts, both of which have been used as control conditions, should be considered comparable or distinct peer contexts.

Modality of Peer Presence (Qualitative: Physically Present, Online, or Otherwise Not Present but Observing Behavior). We identified how peers were incorporated into the decision context and coded this variable with two categories: *physically present*, indicating that peers were physically present in the same room and observing participants’ choices; and *online or otherwise not present, but observing behavior*, indicating that participants were led to believe that peers were remotely or virtually present and observing their choices. This moderator was included to evaluate whether virtual peer observation, which is increasingly used in experimental research to induce the psychological experience of peer observation, produced similar or distinct effect sizes compared to the physical presence of peers.

Number of Peers (Quantitative: Ranging From 1 to 5). We coded the number of peers present in the observed condition. Real-world driving statistics show increased crash rates among male teenage drivers with multiple passengers present in the car (Ferguson, 2013). It has been suggested that peers contribute to a distracting and chaotic decision-making environment that promotes driving in a riskier manner (Ross et al., 2016). This moderator was included to evaluate whether increasing the quantity of peers present in the decision-making context is associated with greater effect sizes.

Gender of Peers Relative to the Participant (Qualitative: Same, Opposite, Mixed). We identified the reported gender of the peers and coded this information relative to the reported gender of the participants using three categories: *same*, *opposite*, and *mixed*, which applied to cases where the peer groups contained individuals who were both the same and the opposite genders of the participants. Most studies described peers in binary terms and did not differentiate between their sex and gender, so we will describe these findings according to gender. Because adolescence is associated with the emergence of romantic desire, some studies have restricted participation to friend-pairs of the same gender to reduce motivations brought on by (heterosexual) romantic feelings (Harakeh & de Boer, 2019). This moderator was included to evaluate whether same and opposite gender peers had differential influence on the effect size.

Whether Peers Were Known to the Participant (Qualitative: Yes, No, Other: Mixed Levels of Familiarity). We identified whether participants knew the peers who were present in the peer

contexts before the study, and coded this variable with three categories: *yes* (e.g., if the participant coparticipated with a friend); *no* (e.g., if the peers were other recruited participants assigned by the experimenter); and *other: mixed levels of familiarity* (e.g., when the peer group included individuals who were known and unknown to the participant before the study). Although adolescents are more likely to engage in activities like driving with friends in their daily lives relative to unfamiliar peers (Ouimet et al., 2013), prior work has suggested that interacting with friends and interacting with unfamiliar peers may elevate risk-taking in similar ways and through the same mechanism of enhancing reward-seeking preferences (Weigard et al., 2014). This moderator was included to evaluate whether known versus unknown peers had differential influence on the effect size.

Risk Preference Displayed by Peer (Qualitative: Pro-Risk, Antirisk, Neutral). We determined whether peers transmitted norms (either verbally or nonverbally) that endorsed or opposed risky behavior before or during the task and coded this variable with three categories: *pro-risk* if the peers communicated a preference for risky behavior, *antirisk* if peers displayed a preference for safe behavior, and *neutral* if peers provided comments that were unrelated to performance or task-related decisions (e.g., “This game is cool.”). For the purposes of moderation analyses, the neutral contexts and contexts in which the peer does not communicate with the participant were combined into the “neutral” moderator level encapsulating studies that did not manipulate expression of peer risk preference.

Prior work has pointed to both direct (e.g., encouragement, reinforcement, approval or disapproval about choices) and indirect (e.g., modeling, observation) mechanisms through which communicated norms may operate during peer observation to shape adolescent risk taking (Borsari & Carey, 2001; Brechwald & Prinstein, 2011; Dishion & Tipsord, 2011; McCoy & Natsuaki, 2018; Reynolds et al., 2014). This moderator was included to evaluate whether peers who display pro-risk norms and peers who display antirisk norms had differential influence on the effect size relative to contexts involving neutral and no commentary from peers.

Analyses focused on this set of structural and theoretically driven moderators. We recorded additional descriptive features of the studies, which are included in the meta-analytic coded data on Open Science Framework (OSF).

Calculation of Effect Sizes

Individual effect sizes and variances were calculated to capture the difference in decision-making under risk between the observed and unobserved conditions. As an index of effect size, Cohen’s d was computed for each comparison and then transformed to Hedges’ g to correct for the bias of inflated effect sizes that may occur with small samples [Formulas 4.22–4.24 in Borenstein et al., (2010)]. Effect sizes were coded directionally such that positive effect sizes indicated increased risk taking in the observed relative to unobserved condition and negative effect sizes indicated reduced risk taking in the observed condition.

Following standard meta-analytic procedures (Lipsey & Wilson, 2001), whenever possible we calculated the effect size and variance using condition means and standard deviations. If the necessary statistics were available only in graphical form, we derived numerical results using Plot Digitizer software (<https://plotdigitizer.com>),

a method commonly used to extract statistical information for use in meta-analyses (Quintana, 2015). If the necessary descriptive statistics could not be derived from text or graphs, authors were contacted by email. We contacted corresponding authors (with two exceptions because the studies contained all of the necessary information: Bexkens et al., 2019; Wagemaker et al., 2020) to request additional information to code moderators and calculate effect sizes. We received the necessary information from 97% of contacted authors. Information obtained from authors appears in the “Log of Data Provided by Authors” file in the online archive.

Information to compute Cohen’s d was derived as follows:

Between-Subjects Designs

Based on means and standard deviations [Formula 2 in Morris and DeShon (2002); Formula 1 in Lakens (2013)].

Within-Subjects Designs

Based on means, standard deviations, and the correlation between the observed and the unobserved condition [r ; Formula 4 and Formula 11 in Morris and DeShon (2002); Formula 9 in Lakens (2013)]. If r was not provided, it was computed using the mean and the standard deviation of both conditions as well as the paired t -statistics [Formulas 24–26 in Morris and DeShon (2002)]. If we were unable to derive the correlation, we contacted authors to request it.

Mixed-Effects Models

Some studies reported results from linear mixed-effects models, typically when accounting for statistical dependency in the data introduced by participant recruitment procedures or multiple measurements per participant. Because computing effect sizes and variances for linear mixed-effects models requires information that is not commonly reported in published articles (e.g., variances of the random effects), we contacted authors to request these values or access to the de-identified raw data that we then reanalyzed, using a linear mixed-effects model analysis with peer observation condition as a fixed factor and a maximal random-effects structure as recommended by Barr et al. (2013). In case of convergence warnings, we followed the standard procedures for using mixed-effects models documented by Figner et al. (2020).

Cohen’s d for mixed-effects models was computed using the formulas provided in Westfall et al. (2014); see also Brysbaert and Stevens (2018). As proposed in Pustejovsky (2016), the corresponding sampling variance was calculated using a delta-method approximation for the asymptotic variance of d . Computing the variance and transforming Cohen’s d into Hedges’ g requires degrees of freedom, which are often inaccessible without access to the full details of one’s study design and/or raw data. To apply a conservative estimate, we used the number of clusters per study. If data were nested in multiple clusters (i.e., in participants and groups), we used the smaller value to be conservative.

Odds Ratios

Some studies reported results for categorical outcome variables (e.g., whether or not the participant passed a car in a driving simulator task) as odds ratios. Odds ratios and variances were transformed into Cohen’s d and its corresponding variance using

the formulas reported in Borenstein et al. (2009); Formulas 7.1 and 7.2.

If the information necessary for effect size calculation was not reported, we contacted authors to request the de-identified raw data and then conducted a generalized linear model analysis using peer observation condition as a main effect. If the data were nested (introduced by participant recruitment procedures or multiple measurements per participant), we conducted a generalized linear mixed-effects model analysis with peer observation condition as a fixed factor and a maximal random-effects structure as recommended by Barr et al. (2013). The derived odds ratio and variance were then transformed into Cohen's d and its variance (Borenstein et al., 2009; Formulas 7.1 and 7.2).

Comparability of Effect Sizes Across Study Designs

Combining effect sizes across different study designs/statistical approaches in a meta-analysis requires special considerations to ensure their comparability. We were able to combine effect sizes derived using between- and within-subjects formulas because the following criteria as outlined in Morris and DeShon (2002) were met: (a) effect sizes were transformed into a common metric (between-subjects metric), (b) the same effect of interest was measured across both types of designs, and (c) sampling variances were estimated based on the original design of the experimental study (Table 1 in Morris & DeShon, 2002).

The final set of studies includes effect sizes that were derived using traditional between-subjects formulas, within-subjects formulas, linear mixed-effects models, generalized linear models, and generalized linear mixed-effects models.⁴ To evaluate comparability of effect sizes in the present meta-analysis, we further investigated whether effect sizes derived using these five different analytical approaches are comparable using a metaregression model with analytical approach as a predictor. We interpret the nonsignificant effect of study design, $F(4, 5.4) = .72, p = .61$, as evidence that the included effect sizes can be meta-analytically combined in one analysis (see Supplemental Figures 1a–b).

Statistical Analysis

All statistical analyses were computed in R Version 4.0.2 (2020-06-22; R Core Team, 2020).

Evaluation of Collinearity

We examined the correlations between moderators to evaluate whether there was underlying structure to the moderators that would constrain interpretation of moderation results. We note that moderators were tested one-at-a-time in the statistical models, so collinearity analyses are meant to describe the general associations among moderators rather than serve as a diagnostic check of the models themselves. We preregistered $|r| > .5$ as the threshold for deeming two variables collinear. Though there were a small number of correlations above $|r| > .5$ among moderators (e.g., driving studies tended not to include incentive compatibility; excitement ratings tended to be higher for tasks providing immediate feedback), the vast majority of correlations were below that threshold, and the moderators showing significant effects did not exhibit collinearity

with any of the other moderators. Collinearity results are described in Supplemental Table 3.

Robust Variance Estimation

Several studies included in the meta-analysis provided multiple effect size estimates from the same sample of participants. In addition, some correspondence with authors revealed that the same sample of participants completed tasks reported in multiple published articles included in the meta-analysis. Thus, the 186 effect sizes from 53 distinct reports were not fully statistically independent but nested within 52 samples, thereby violating traditional assumptions of independence. To allow for the inclusion of all reported effect sizes, we employed robust variance estimation (RVE) procedures as implemented in *robuneta* Version 2.0 (Fisher et al., 2017), a widely adopted meta-analytic approach that accounts for statistical dependency between effect sizes by adjusting study standard errors when the correlation between effect sizes are unknown (Hedges et al., 2010).

Weighting Scheme

The dependency in the data was predominantly caused by multiple dependent variables being reported from the same participant sample. For example, Centifanti and Modecki (2013) report results from participants conducting the BART and Centifanti et al. (2016) report results from the same participants conducting the Stoplight driving task, thereby introducing dependency between the effect sizes derived from both articles. To account for this dependency, we employed correlated weights in the analyses (Hedges et al., 2010; Tanner-Smith & Tipton, 2014). Correlated weights are recommended when studies provide multiple effect sizes from the same underlying construct of interest. This was the case for several studies that provided multiple effect sizes from the same sample of participants or explicitly noted that the same sample of participants completed tasks reported across other published articles included in the meta-analysis.

Within-Study Effect Size Correlation

As recommended by Tanner-Smith and Tipton (2014), the within-study effect size correlation (ρ , estimate for the complex and often unknown correlations among nonindependent effect sizes) was fixed to 0.80. To determine the impact of the assumed correlation, we performed sensitivity analyses on the overall effect metaregression model, testing for different values of ρ ($\rho = 0, 0.20, 0.40, 0.60, 0.80$). The significance of the estimated effect size did not change, so we continued to use $\rho = 0.80$ for the remaining analyses.

Small Sample Size Correction

RVE procedures for estimating metaregression coefficients perform best with at least 40 samples with an average of five effect sizes per sample (Tanner-Smith & Tipton, 2014). Since we

⁴ Because no transformations are available for effect sizes derived via linear mixed-effects models, generalized linear models, and generalized linear mixed-effects models, effect sizes calculated via these approaches are an exception to the guidelines described above.

Table 1
Descriptive Information About Moderators Tested in Meta-Analysis

Moderator descriptives	Number of effect sizes included	%
Publication-level moderators		
Publication status		
Published	129	69.4
Unpublished	57	30.6
Study design		
Between	65	34.9
Within	69	37.1
Mixed/other	52	28.0
Task-level moderators		
Task approach		
Driving-game	37	19.9
Driving-simulation	72	38.7
Economics-static	28	15.1
Economics-dynamic	49	26.3
Incentive compatibility		
Concrete outcome available	77	41.8
No concrete outcome available	107	58.2
Optimal task strategy		
More risky choices	15	16.5
Risky up to a point	23	25.3
More safe choices	38	41.8
Risky and safe equivalent	15	16.5
Outcome probabilities		
Known	33	17.8
Unknown	153	82.2
Immediate performance feedback		
Provided	130	70.3
Not provided	55	29.7
Safe option availability		
Available	7	3.8
Not available	179	96.2
Subjective excitement		
1	5	2.7
2	25	13.4
3	10	5.4
4	40	21.5
5	36	19.4
6	23	12.4
7	47	25.3
Peer-level moderators		
Unobserved condition		
Alone	171	91.9
Group testing	15	8.1
Modality of peer presence		
Physically present	134	72.0
Online or otherwise not physically present	52	28.0
Number of peers		
1	135	72.6
2	29	21.0
3	10	5.4
4	0	0
5	2	1.0
Gender of peers relative to participant		
Same	131	70.4
Opposite	14	7.5
Mixed: Both same and opposite	41	22.0
Familiarity of peers to participant		
Familiar	52	28.0
Unfamiliar	114	61.3
Mixed	20	10.7
Risk preference displayed by peer		
Pro-risk	45	24.9
Antirisk	17	9.4
Neutral/none	119	65.7

include 52 samples with an average of 3.58 effect sizes per sample, the RVE procedures applied to our sample may yield too narrow confidence intervals resulting in excessively small p values. To protect against a heightened risk of Type 1 error and in line with the recommendation to include small-sample size corrections when using RVE procedures (Tanner-Smith et al., 2016), we used a small-sample size correction that adjusts the estimator and implements Satterthwaite approximated degrees of freedom (Satterthwaite, 1946; Tipton, 2015). The estimated degrees of freedom indicated whether the results can be trusted: when there were more than four degrees of freedom, RVE could be used to estimate metaregression models. Yet, if there were four or fewer degrees of freedom for a specific moderator, we adjusted the α -level for determining statistical significance for that moderator to $p < .01$ as recommended by Tipton (2015).

Heterogeneity of Effect Sizes

Investigating the heterogeneity of effect sizes is crucial from a conceptual and statistical standpoint. Conceptually, high heterogeneity highlights the importance of investigating the specific moderating conditions under which peer observation influences adolescent risky decision-making. Statistically, a high degree of heterogeneity confirms the necessity of using random-effects models since these models allow for the generalization of effect sizes by capturing their variation beyond sampling variability. To quantify the percentage of variance due to true heterogeneity as opposed to random sampling error, we computed the I^2 value and τ^2 value for the main model, which was $I^2 = 82.63\%$ and $\tau^2 = 0.078$. While an I^2 value of 0 indicates no heterogeneity, a value greater than 50% indicates a moderate degree of heterogeneity, and a value greater than 75% indicates high heterogeneity (Higgins et al., 2003). Thus, the effect sizes considered here are highly variable, further motivating the moderator analyses conducted and the use of random-effects models.

Testing Overall Effects and Moderators

First, analyses quantified the overall effect size of direct peer observation by fitting an intercept-only random-effects model using RVE procedures and small-sample size correction (Tanner-Smith et al., 2016). The intercept of this model was adjusted for correlated-effect dependencies and represents a precision-weighted overall effect size.

Second, we tested the significance of the effects of each moderator described in the Method section, using RVE metaregression models including only the moderator of interest as a predictor.^{5,6} For each moderator analysis, we excluded effect sizes with a missing value on that specific moderator. Significance tests related to the regression coefficients of these predictors indicate whether the variables are significant moderators of peer effects on adolescent

⁵ Note that moderator analyses typically need a large number of observations to achieve sufficient power (Hedges & Pigott, 2004). High levels of heterogeneity as well as the use of RVE procedures further reduce the power to detect significant moderators and null effects should thus be interpreted with caution (Coles et al., 2019).

⁶ An exception is the metaregression model investigating linear and nonlinear influences of age on the magnitude of the effect of peer observation. In this model, we simultaneously include linear and quadratic polynomial predictors of age (created using the *poly* command in R).

risky decisions. Continuous moderators were standardized, and categorical moderators were dummy coded and added to the meta-regression equations. Parameter estimates (b) for moderators of interest are reported in unstandardized units. Significant effects are expressed in units of Hedges' g .

In the case of dummy coding moderators with more than two levels, the resulting regression coefficients test the difference between a single level of a moderator and a single comparison level. Therefore, and as recommended by Tanner-Smith et al. (2016), we also performed F tests for categorical moderators with more than two levels using the *clubSandwich* package Version 0.5.2 (Pustejovsky, 2017), which indicated whether there is a difference among all levels of the moderator. To facilitate the interpretation of significant moderators, we estimated the overall effect size of the observed versus unobserved effect by fitting an intercept-only random-effects model on each level of significant categorical moderators.

Inference Criteria

We used the standard inference criterion of $p < .05$. If a meta-regression model had four or fewer degrees of freedom, we adjusted the α -level for determining statistical significance for this model to $p < .01$ (as recommended in Tipton, 2015). In practice, this adjustment did not meaningfully alter the significance of any result. For more information, see the section above on small-sample size correction.

Quantification of Publication Bias

We followed Rodgers and Pustejovsky (2020) recommendations for detecting publication bias with dependent effect sizes. First, we implemented a combination of Egger's regression test (Egger et al., 1997) and RVE procedures (Fisher et al., 2017) to assess funnel plot asymmetry. More specifically, we included a measure of effect size precision (standard error) in the meta-regression equation, estimated the slope of this predictor, and tested for its significance. This test has two notable limitations. First, funnel plot asymmetry is not only indicative of selective reporting but could also be attributed to other causes such as high between-study heterogeneity or study design differences. Second, this test might suffer from a lack of power when nonsignificant effects are not reported.

In addition to Egger's regression test for funnel plot asymmetry, we implemented Vevea and Hedges (1995) three-parameter model, which provides greater power and can be interpreted as a more direct test of publication bias. This model was fit to all published effect sizes, using a one-sided cut-off parameter at $p < .05$, assuming greater effect sizes for published effects. To fulfill the assumption of statistical independence of effect sizes, we randomly sampled one effect size from each study to generate a set of effect sizes, conducted the three-parameter model on each set of 41 published effect sizes, and repeated the procedure 1,000 times. The reported χ^2 statistic is associated with the median model.

To complement traditional tests of publication bias, we additionally evaluated whether publication status (*report published*, *report unpublished*) moderated the overall effect size of peer observation on risky decisions.

Results

Screening and Selection Procedure

Figure 1 presents the diagram summarizing the selection and exclusion process in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (Moher et al., 2009). Through the literature searches and unpublished data requests, we identified 3,893 reports, following the removal of duplicates. All reports were screened briefly for relevance by reading the titles and abstracts or study description(s) provided by the authors (for unpublished work), and reports of studies that clearly did not meet the inclusion criteria were excluded at this stage ($n = 3,420$ excluded). Reports of studies passing this first screening ($n = 473$) were assessed for the inclusion criteria more closely. Cases in which the same sample and dependent variable appeared in multiple studies were identified as redundant samples and excluded at this stage ($n = 10$). These occurred when the same study existed as both a published article and an unpublished data set, thesis, or dissertation (in which case, the published version was carried forward for inclusion), and when the same participants and dependent measures were included in multiple published articles (e.g., one article reporting behavioral findings and one reporting behavioral and functional magnetic resonance imaging findings). In these cases, the report with the largest sample size was carried forward for inclusion.

This search, screening, and selection procedure yielded 56 reports of at least one study that satisfied inclusion criteria. Of these, three were excluded from final analyses due to missing statistical information needed to calculate effect sizes. Thus, there was a final sample of 53 reports with 186 comparisons. Some reports contained more than one individual study meeting inclusion criteria; in total, 62 individual studies were included within these reports. The final included effect sizes are listed in Supplemental Table 1 and provided in full detail in the "Coded Moderators and Effect Sizes" file on OSF.

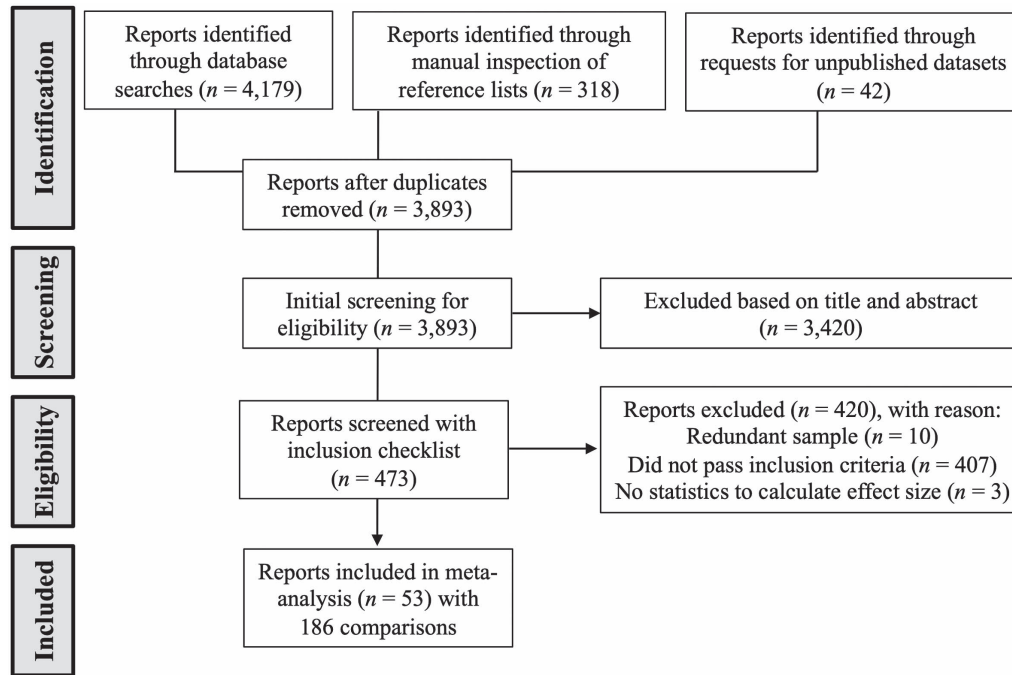
Descriptive Overview of Synthesized Research

This meta-analysis analyzes across a total of 186 effect sizes, derived from 53 distinct reports of 62 studies with 52 unique participant samples, and representing data from 5,531 participants.⁷ The wide criterion age analysis represents studies with samples for which the *mean age* fell within 10–19 years ($M = 16.92$ years, range = 8.3–25.0 years) and the narrow criterion age analysis represents studies with samples for which the *full age range* fell within 10–19 years ($M = 15.71$ years). Results synthesize findings from published and unpublished reports, with more effect sizes deriving from published work (40 reports) than unpublished work (13 reports). Unpublished work included PhD dissertations, honors theses, conference proceedings, working data sets, and articles in-preparation or under review. See Table 2 and Figure 2 for descriptive demographic statistics, and Supplemental Table 1 for a log of all included effect sizes. See Table 1 for descriptive statistics on the moderators used in the analyses.

⁷ This value is a best-guess approximation, as certain reports did not have sufficient information to track exclusions across individuals who completed multiple tasks. In these cases, the sum uses the sample size from the largest task, but it remains possible that within a sample, data from participants excluded from one task counted toward the sample size of a separate task in that report.

Figure 1

Preferred Reporting Items for Systematic Reviews Meta-Analyses (PRISMA) Diagram Depicting the Study Selection and Exclusion Process



Note. Lower case *n* denotes individual reports. The initial screening criteria for eligibility were: (a) Reports included a sample of adolescent participants, (b) Reports contained an experimental decision-making task that measured risky decision-making, (c) Reports contained an experimental manipulation of peer observation during the task. The next, more comprehensive screening using the full inclusion checklist included reconfirming (a–c), and (d) Reports contained (or authors provided) sufficient statistics to calculate the effect size for the difference in risk taking between the observed and unobserved conditions, (e) Reports contained a nonclinical participant sample, and (f) Reports were written in English. If reports (i.e., publication level products) included the results of multiple studies (i.e., data sets), each study was screened individually. A total of 62 studies reported within the 53 reports met inclusion criteria.

This meta-analysis represents data collected in seven countries across four continents, including English-speaking and non-English-speaking locations: North America (United States, Canada); Europe (United Kingdom, Netherlands, Belgium, Germany); Asia (China), and Australia. Most effect sizes were derived from research conducted in the United States and in Europe.

Race and ethnicity demographic information was not presented consistently within these reports. When this information was available (in approximately 50% of studies, largely drawing from North American samples), we observed a great deal of variation in the level of detail provided. Descriptions ranged from precise numerical percentages quantifying the racial and

ethnic composition of the samples to broad summary statements (e.g., “Participants were mostly Caucasian.”).

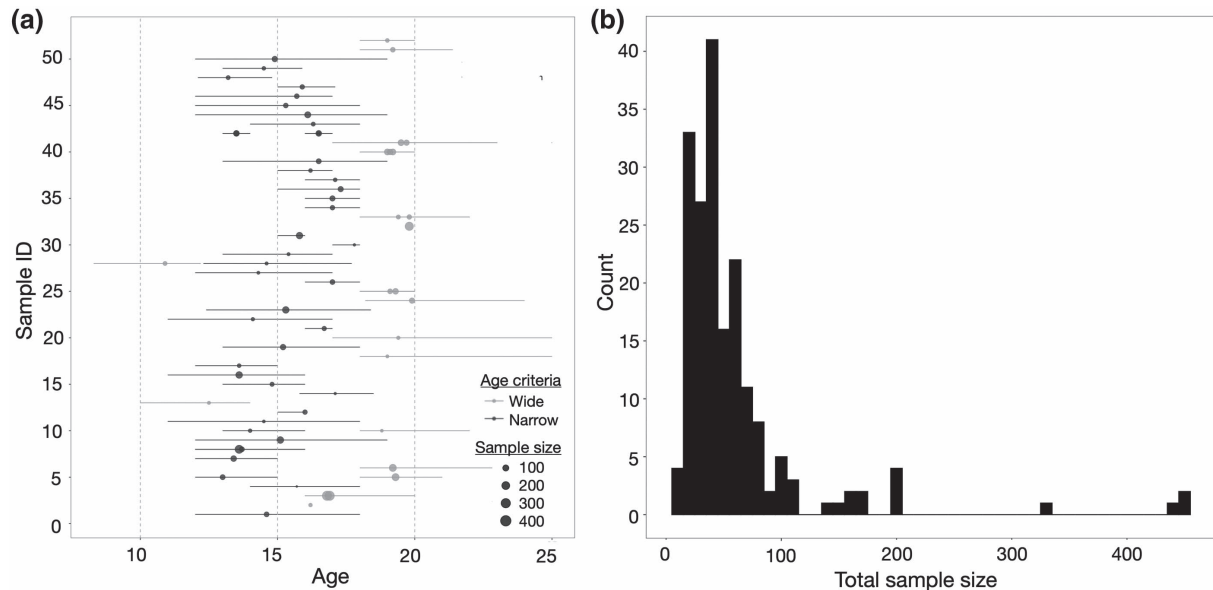
In terms of experimental tasks, both economic and naturalistic driving approaches to characterizing risk taking were well-represented in the literature, with researchers selecting tasks with economic frameworks slightly more frequently. The measurement properties and external validity properties are unknown for many of the tasks represented in this meta-analysis. [Supplemental Table 2](#) summarizes the nascent understanding of the measurement properties for the tasks included in the meta-analysis. For additional review and perspectives on laboratory behavioral risk-taking tasks, see [Charness et al. \(2013\)](#), [Dahne et al. \(2013\)](#), and [Defoe et al. \(2015\)](#).

Table 2

Descriptive Characteristics of Data Included in Meta-Analysis

Sample descriptives	Number of reports	Number of effect sizes	<i>M</i>	<i>SD</i>	Minimum	Maximum
Sample size	53	186	59.79	65.09	13	452
Gender composition (% female)	53	186	41.92	31.67	0	100
<i>M</i> _{age} (narrow analysis)	38	113	15.71	1.49	12.45	17.80
<i>M</i> _{age} (wide analysis)	53	186	16.92	2.13	10.90	19.90

Figure 2
Descriptive Plots of Participant Samples Included in the Meta-Analysis



Note. (a) Sample size and age distribution for each sample. Each row represents a unique sample, with the Sample ID on the y-axis corresponding to the Sample ID in the meta-analytic data file. The location of each dot indicates the mean age of the sample (Along x-axis) and the size of each dot indicating the size of the sample. Horizontal lines denote the full age range. Rows with multiple dots denote samples with multiple sub-groups, in which case multiple mean ages are shown. Black lines and dots indicate samples that fall within the “narrow” age criterion (full sample falling within 10–19 years) and gray lines and dots indicate samples that fall within the wide criterion (mean age falling within 10–19 years). For two reports that did not provide the sample’s age range, the mean is plotted without horizontal range lines. These are sample ID no. 2 (Cavalca et al., 2013) and sample ID no. 32 (Shepherd et al., 2011). (b) Histogram of total sample sizes of all unique samples included in the meta-analysis (wide criterion).

Studies commonly reported multiple dependent variables derived from a single risk-taking task (e.g., pumps and explosions in the BART task; accidents, average speed, and maximum speed in a driving simulator task). Several reports ($n = 5$) included the results from multiple tasks, and may reflect a desire to examine the specificity of peer effects across multiple decision-making contexts. In these cases, a combination of tasks spanning both economic and driving frameworks was typically reported.

We observed substantial variability surrounding descriptions of peer configurations and the ways in which peers were incorporated into experimental designs. Though the present meta-analysis uses the terms “observed” and “unobserved” to describe the presence or absence of a peer observer in experimental conditions, researchers utilized diverse terminology to refer to these peer conditions across studies. For example, the “observed” condition was labeled as *peer*, *group*, *observed*, *watched*, and *together*, whereas the “unobserved” condition was labeled as *alone*, *solo*, *independent*, *private*, and *control*. This broad range of terminology used to describe common features of these experimental conditions makes literatures searches more challenging and may reflect researchers’ diverse conceptions of peer observation. In addition to these two core peer conditions of focus (*observed and unobserved*)—that were included in all studies by definition—25 studies included additional conditions targeting different combinations of moderators related to peer involvement (e.g., a condition with a virtual peer observing and a condition with a physically present peer observing).

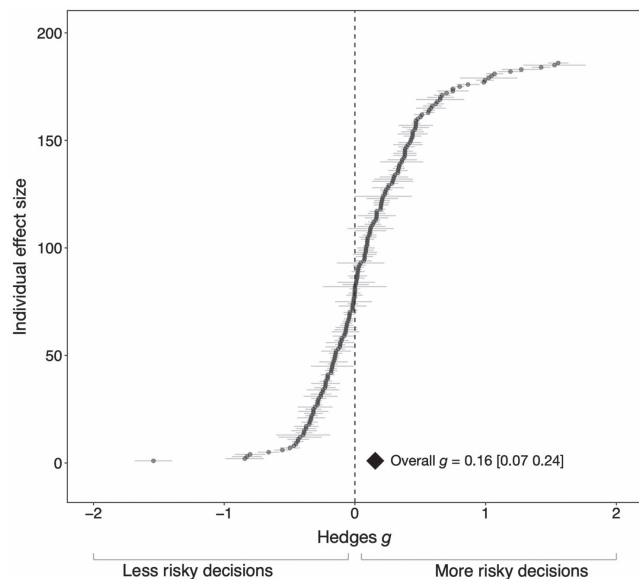
Overall Effect of Peer Observation on Adolescent Risky Decision-Making

The primary aim was to quantify the magnitude of the mean effect of peer observation on adolescent risky decisions, relative to decisions made alone. Effect sizes ranged from -1.54 to 1.56 , with positive values indicating increased risk taking in the observed relative to unobserved condition. Results from the RVE random-effects model indicated that peer observation significantly increased risky decision-making (Hedges’ $g = .16$, $p < .001$, 95% CI [0.07, 0.24]). Hedges’ g values less than 0.2 are generally interpreted as small effects. When expressed as the equivalent odds ratio, this mean effect size indicates that participants are 1.31 times as likely to engage in a risky choice while under the observation of peers compared to when alone. See Figure 3 and Supplemental Table 2 for a full list of computed effect sizes.

Moderator Analyses

Our second aim was to investigate key moderators that may amplify or reduce the effect of peer observation on adolescent decisions about risk. Analyses targeted characteristics related to the (a) publication status, (b) sample, (c) decision task, and (d) peers. Results from all statistical models are summarized in Table 3.

Figure 3
Caterpillar Plot of All 186 Included Effect Sizes and Overall Meta-Analytic Effect



Note. The overall effect size is indicated by the black diamond. Each dot represents an effect size; bars indicate 95% CI. Because of the large number of effect sizes, publication is not included on the y-axis. Individual effect sizes are sorted by value to enhance readability. Along the x-axis, positive values indicate more risky choices during peer observation than no observation; negative values indicate more risky choices during no observation than during peer observation. CI = confidence interval.

Publication-Level Moderators

Publication Status

See below in Analysis of Publication Bias.

Year

We evaluated whether the year of publication (or year of retrieval for unpublished work) moderated the overall effect size of peer observation on risky decision-making in adolescents. Most reports were published between 2011 and 2020, with two publications in 2005 (see Supplemental Figure 2). Visual inspection of the plotted effect sizes indicated a negative slope, but we did not find evidence that publication year significantly moderated the overall effect ($b = -0.08$, $p = .065$, 95% CI $[-0.17, 0.01]$). The significance of results does not change if unpublished reports are omitted from this analysis.

Sample-Level Moderators

We evaluated whether characteristics related to the sample moderated the overall mean effect size of peer observation on adolescent decisions to take risks in a series of RVE meta-regression models. We tested three sample-level moderators including sample size, gender composition, and mean age, with the models evaluating sample size and gender composition models treating the moderator of interest as a single predictor and the model evaluating mean age simultaneously

testing the linear and quadratic age predictors (see Supplemental Figure 3).

Sample Size

Most sample sizes fell on the smaller end of the full spectrum, ranging from $N = 13$ to $N = 452$ ($M = 59.79$, $SD = 65.09$), with few studies reporting on very large samples (see Figure 2b; Supplemental Figure 2). We did not observe a significant effect of sample size on adolescent decisions to take risks under peer observation ($b = -0.005$, $p = .91$, 95% CI $[-0.14, 0.13]$; Supplemental Figure 3a). The negatively signed test statistic indicates that nominally, larger samples are associated with smaller effect sizes, though this effect is not significant. Note that due to the insufficient degrees of freedom, this result should not be interpreted.

Gender Composition

Of the 62 studies included in the meta-analysis, 16 reported 100% male samples, four reported a 100% female sample, and 42 reported samples containing male and female participants. The overall percentage of female participants included across all studies was 41.92%. Gender composition did not significantly moderate the mean effect size ($b = 0.006$, $p = .88$, 95% CI $[-0.08, 0.09]$; Supplemental Figure 3b).

Mean Age

We tested whether effect sizes varied as a function of the mean age of the sample to determine whether younger or older adolescence might be associated with greater effect sizes relative to other phases. We did not observe a moderating effect of age for the linear predictor ($b = 0.06$, $p = .21$, 95% CI $[-0.03, .014]$; Supplemental Figure 3c-d) or the quadratic predictor ($b = -0.05$, $p = .25$, 95% CI $[-0.13, 0.04]$; Supplemental Figure 3c-d).

Summary

Synthesizing across all studies, we found no evidence of systematic effects of sample-level factors on decisions to take risks under peer observation.

Risky Decision-Making Task-Level Moderators

We evaluated seven potential moderating characteristics of risky decision-making tasks in a series of RVE meta-regression models. These variables varied across reports as well as within studies (e.g., when a single report included results from multiple tasks, or a single task contained multiple conditions manipulating a relevant dimension). Effect sizes for task-level moderators are depicted in Figure 4.

Task Approach

We tested whether the task design was informed by economic or ecological frameworks. There were a total of 186 effect sizes included in this test. Results did not reveal an effect of the task approach on the mean effect of peer observation on adolescent risky decisions, $F(3, 26.22) = 1.36$, $p = .28$; Figure 4a.

Table 3
Results of Moderator Analyses

Moderator	Number of effect sizes	Test statistic	Degrees of freedom	<i>p</i> value	95% CI [lower, upper]
Publication-level moderators					
Publication status	186	$b = -0.17$	14.15	.020	[-0.30, -0.03]
Year	186	$b = -0.08$	20.25	.065	[-0.17, 0.01]
Sample-level moderators					
Sample size ^a	186	$b = -0.005$	3.01	.91	[-0.14, 0.13]
Gender composition (% female)	186	$b = 0.006$	20.42	.88	[-0.08, 0.09]
Mean participant age—linear	186	$b = 0.06$	20.83	.21	[-0.03, 0.14]
Mean participant age—quadratic	186	$b = -0.05$	10.42	.25	[-0.13, 0.04]
Task-level moderators					
Task approach	186	$F = 1.36$	3, 26.22	.28	—
Economics (static, dynamic), driving (simulation, games)					
Incentive compatibility	184	$b = -.011$	38.40	.16	[-0.28, 0.05]
Concrete outcome available, no concrete outcome available					
Optimal task strategy	91	$F = 1.33$	3, 15.30	.30	—
More risky decisions, more safe decisions, more risky decisions up to a point, risky and safe decisions equally optimal					
Choice probabilities	186	$b = .05$	19.75	.57	[-.14, .24]
Known, unknown					
Immediate performance feedback	185	$b = -.13$	13.60	.077	[-.29, .02]
Provided, not provided					
Safe option availability ^a	186	$b = -.19$	2.27	.48	[-1.04, .67]
Available, not available					
Excitement rating	186	$b = .001$	20.29	.98	[-.09, .09]
1 (not at all) to 7 (very)					
Peer-level moderators					
Unobserved condition	186	$b = -.08$	5.92	.59	[-.45, .28]
Alone, group testing					
Peer presence modality	186	$b = -.05$	35.39	.64	[-.25, .16]
Physically, virtually present					
Number of peers	186	$b = .002$	6.04	.95	[-.09, .09]
Gender of peers	186	$F = .80$	2, 1.93	.56	—
Same, opposite, mixed					
Peer familiarity	186	$F = .08$	2, 14.52	.92	—
Known, unknown, mixed					
Risk preferences displayed by peers	181	$F = 6.27$	2, 11.2	.01	—
Pro-risk, antirisk, neutral					

Note. CI = confidence interval. Bold text indicates $p < .05$ significance.

^aRegression model contains fewer than four degrees of freedom and should not be interpreted.

Incentive Compatibility

We evaluated whether tasks that presented participants with a concrete outcome tied to their task performance (e.g., bonus money) differentially affected willingness to take risks under peer observation. There were a total of 184 effect sizes included in this test (for two effect sizes, not enough information was available to code this moderator). We did not find evidence that the presence of concrete performance-based outcomes significantly moderated the mean effect of peer observation on adolescent risky decisions ($b = -0.11, p = .16, 95\% \text{ CI } [-0.28, 0.05]$; Figure 4b). The negatively signed test statistic indicates that nominally, incentive compatibility is associated with greater effect sizes, though this effect is not significant.

Optimal Strategy

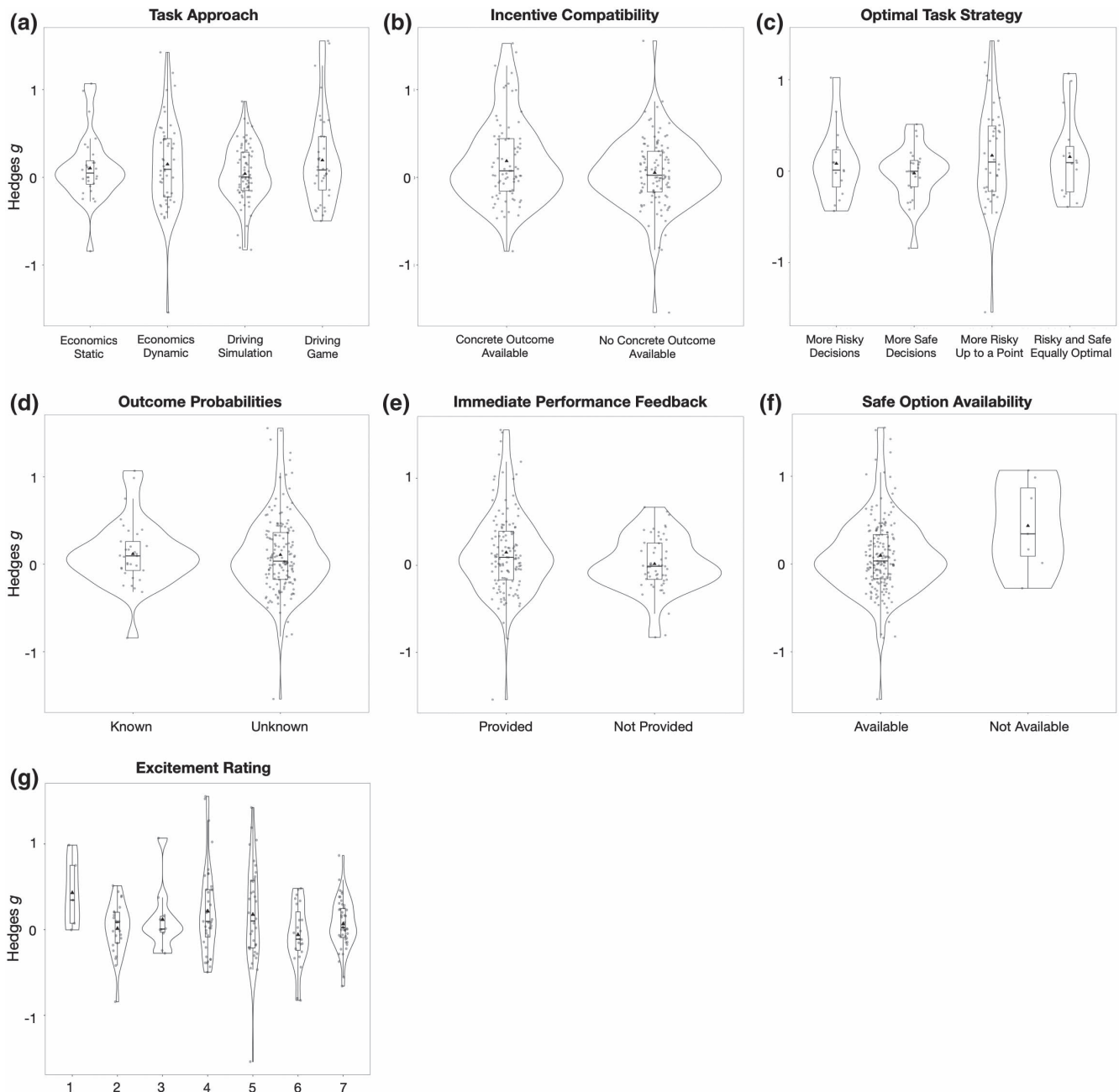
A total of 91 effect sizes were coded according to optimal strategy. Only effect sizes for which it was possible to compute

the expected value of choices were included in this analysis, coded as tasks in which (a) risky decisions were optimal, (b) safe decisions were optimal, (c) risky decisions were optimal up to a certain point, or (d) risky and safe choices were equally optimal. Across these categories, we did not find evidence that optimal task strategy significantly moderated the effect of peer observation on adolescent risky decisions, $F(3, 15.30) = 1.33, p = .30$; Figure 4c.

Choice Probabilities

We evaluated whether the probabilities of choice options were specified (“known”) or unspecified (“unknown”). All 186 effect sizes were included in this moderator analysis. Results revealed that whether the probabilities or choice options were known or unknown did not significantly moderate the mean effect of peer observation on adolescent risky decisions ($b = 0.05, p = .57, 95\% \text{ CI } [-0.14, 0.24]$; Figure 4d).

Figure 4
Plots Depicting the Effect Size Distribution for Each Task-Level Moderator



Note. In the middle of each violin plot is a box plot, with the rectangle showing the ends of the first and third quartiles, the horizontal line representing the median, and the central black dot representing the mean. Each dot represents an individual effect size. The width of the violin plots corresponds to the kernel probability density at different values of Hedges' g . The safe option availability moderator (f) contains fewer than four degrees of freedom and should not be interpreted.

Immediate Performance Feedback

We systematically examined whether tasks that were structured to provide immediate feedback on the outcome of a choice influenced decisions to engage in risk. A total of 185 effect sizes were included in this moderator analysis (insufficient information was available to code one effect size). Though immediate outcome feedback was

associated with a nominally larger mean effect, this result was not significant ($b = -0.13$, $p = .077$, 95% CI $[-0.29, 0.02]$; Figure 4e).

Safe Option Availability

We tested whether or not a safe option (i.e., an option with no associated risk) was available in the choice set. All 186 effect sizes

were included in this moderator analysis. This moderator was unbalanced in favor of tasks containing a safe option, resulting in the low number of 2.27 degrees of freedom. Results did not reveal a significant effect of safe options' availability on adolescent risky decisions under peer observation $b = -0.19$, $p = .48$, 95% CI $[-1.04, 0.67]$; Figure 4f. Note that due to the insufficient degrees of freedom, this result should not be interpreted.

Excitement Rating

The amount of excitement associated with the subjective experience of completing each task was rated on a scale ranging from 1 (*not at all exciting*) to 7 (*very exciting*) based on the task description. All 186 effect sizes were included in this moderator analysis. Ratings encompassed the full range of the scale across the 62 included studies (*minimum* = 1, *maximum* = 7; $M = 4.80$, $SD = 1.78$). We did not find evidence that the excitement level of the task significantly moderated the mean effect of peer observation on adolescent risky decisions ($b = 0.001$, $p = .98$, 95% CI $[-0.09, 0.09]$; Figure 4g).

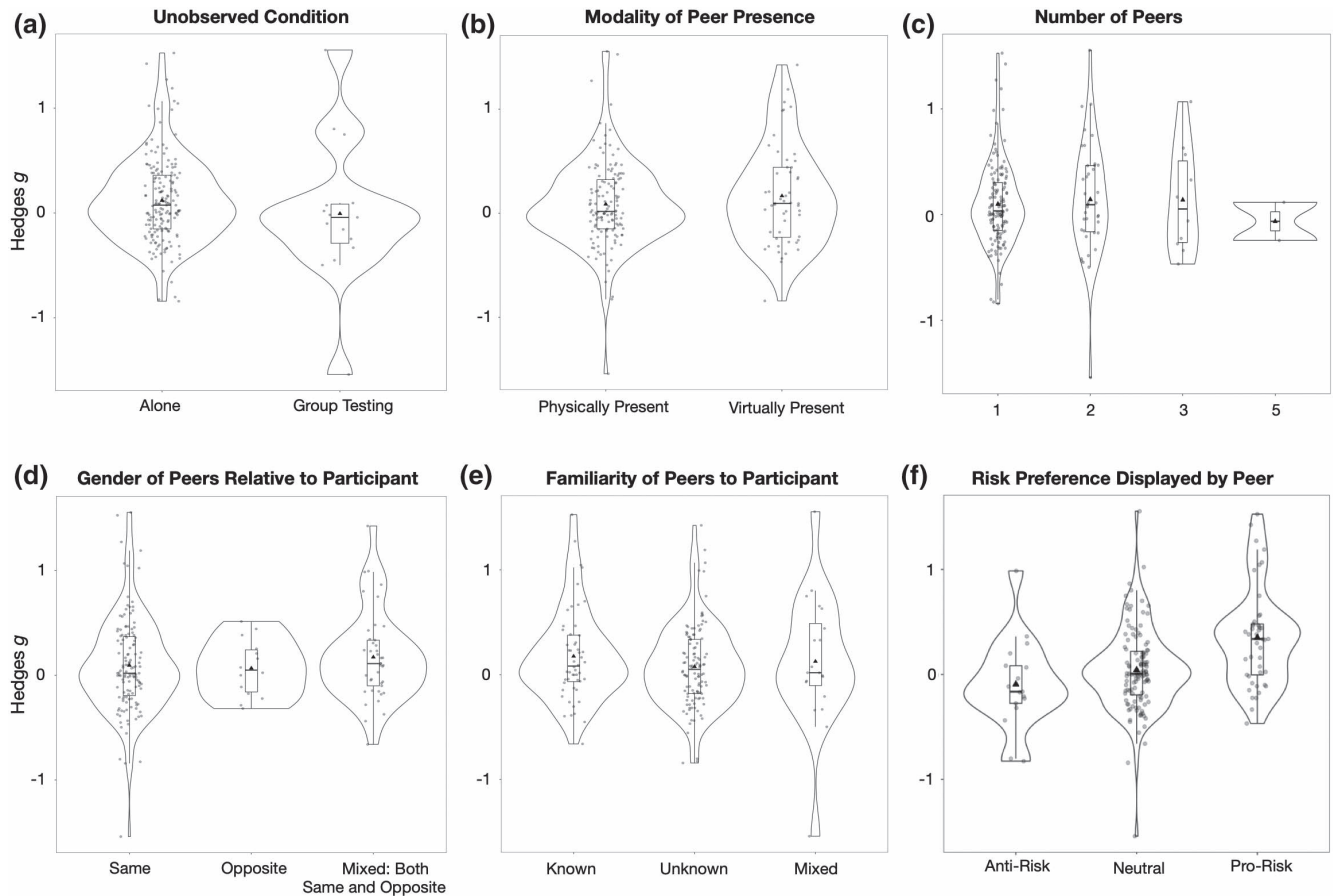
Summary

In summary, for all investigated task-level moderators, results revealed no significant influence on the overall effect size of peer observation on adolescent decisions to take risks. That is, these task-level variations in the decision context did not systematically reduce or amplify adolescents' willingness to engage in risky decisions when under peer observation.

Peer-Level Moderators

We evaluated six potential moderating characteristics related to the nature of peer involvement in a series of RVE meta-regression models. As with the task-level variables, these moderators varied across studies as well as within studies (e.g., when a single report included results from multiple tasks, or a single task contained conditions that manipulated a relevant dimension). Effect sizes for peer-level moderators are depicted in Figure 5.

Figure 5
Plots Depicting the Effect Size Distribution for Each Peer-Level Moderator



Note. In the middle of each violin plot is a box plot, with the rectangle showing the ends of the first and third quartiles, the horizontal line representing the median, and the central black dot representing the mean. Each dot represents an individual effect size. The width of the violin plots corresponds to the kernel probability density at different values of Hedges' g . Along the y-axis, positive values indicate more risky choices during peer observation than no observation; negative values indicate more risky choices during no observation than during peer observation.

Unobserved Condition

We evaluated whether properties of the “unobserved” control condition—in which there was no active peer observation—moderated choices to engage in risky decisions. Specifically, we compared effect sizes that operationalized “unobserved” as decisions made in a room alone (“alone”) versus being in the presence of others who could not observe the participant’s choices (“group testing”). All 186 effect sizes were included in this moderator analysis. We did not find evidence that the configuration of the unobserved condition significantly moderated the mean effect of peer observation on adolescent risky decisions ($b = -0.08$, $p = .59$, 95% CI [-0.45, 0.28]; Figure 5a).

Peer Presence Modality

We compared the impact of peers who were physically present and peers believed to be remotely or virtually present and observing their choices on risky decision-making. All 186 effect sizes were included in this moderator analysis. We did not find evidence that the modality of peer presence significantly moderated the mean effect of peer observation on adolescent risky decisions ($b = -0.046$, $p = .65$, 95% CI [-0.25, 0.16]; Figure 5b).

Number of Peers

We evaluated whether the number of peers present in the decision context systematically influenced decisions to take risks. All 186 effect sizes were included in this moderator analysis. The number of peers ranged from one to five (with the vast majority having one peer). We did not find evidence that the number of peers present to observe risky choices significantly influenced the mean effect of peer observation on adolescents’ risky decisions ($b = 0.002$, $p = .95$, 95% CI [-0.09, 0.09]; Figure 5c).

Gender of Peers Relative to the Participant

All 186 effect sizes were included in this moderator analysis. We did not find evidence that the gender of the observing peers (relative to the participant) significantly moderated the mean effect of peer observation on adolescent decisions about risk, $F(2, 1.93) = 0.80$, $p = .56$; Figure 5d).

Peer Familiarity

We evaluated whether knowing the peer observer(s) impacted the degree to which peer observation influenced adolescent decisions to take risk. All 186 effect sizes were included in this moderator analysis. We did not find evidence that familiarity with the observing peers significantly moderated the mean effect of peer observation on adolescent decisions about risk, $F(2, 14.52) = 0.081$, $p = .92$; Figure 5e).

Risk Preferences Displayed by Peers

Finally, we evaluated whether displays of pro-risk or antirisk preferences by peers before or during the task reliably shifted adolescent decisions to take risks. A total of 181 effect sizes were included in this moderator analysis. Testing this moderator with three categorical levels (pro-risk, antirisk, and neutral) yielded a

significant effect of peer risk preferences on the impact of peer observation on risky decision-making, $F(2, 11.2) = 6.27$, $p = .01$; Figure 5f.⁸ Still, this effect should be interpreted with caution because the analysis is not significant when using the restricted set of 108 effect sizes that fell within narrow age criteria, $F(2, 4.93) = 2.13$, $p = .22$.

Because the main results indicated that peer risk preference significantly moderated the effect of peer observation on risky choice, we conducted nonpreregistered post hoc analyses. Pairwise comparisons between the three levels of this categorical predictor revealed that peers expressing pro-risk attitudes showed a significant increase in risky choice when under peer observation relative to contexts in which peer preferences were neutral or not conveyed ($b = 0.40$, $p = .001$, 95% CI [0.17, 0.62]). There were no significant differences found between pro-risk and antirisk manipulations ($b = 0.34$, $p = .19$, 95% CI [-0.21, 0.88]) or between neutral and antirisk manipulations ($b = 0.06$, $p = .80$, 95% CI [-0.49, 0.61]).

The final set of post hoc analyses decomposed the three-level omnibus test to evaluate zero-order contrasts isolating the effect size for each condition separately. We observed a significant effect of peer observation on risky choices when peers were expressing pro-risk preferences (Hedges’ $g = 0.52$, $p < .001$, 95% CI [0.31, 0.74]). When considering the effect sizes for which neutral no preferences were conveyed, the effect of peer observation was not significant (Hedges’ $g = 0.068$, $p = .09$, 95% CI [-0.01, 0.15]). Within the condition for which peers expressed antirisk preferences, there was no significant effect of peer observation, though it should be noted there were very few effect sizes in this category (Hedges’ $g = 0.039$, $p = .84$, 95% CI [-0.41, 0.48]). The stringent age criteria tests aligned in significance with the results from the wide age criteria reported here.

Summary

For most moderators related to peers, results revealed no significant influence on the overall effect size of peer observation on adolescent decisions to take risks. The crucial exception is in cases where peers are both observing and expressing pro-risk preferences. In this case, peers’ pro-risk preferences increased the effect size from very small/negligible (neutral peers) to medium (pro-risk peers).

Tests for Publication Bias

We assessed funnel plot asymmetry using a combination of Egger’s regression test (Egger et al., 1997) and RVE procedures (Fisher et al., 2017). Egger’s regression test did not provide evidence for publication bias ($b = 1.92$, $p = .54$, 95% CI [-4.82, 8.65], see Supplemental Figure 4a).

In addition, we implemented Vevea and Hedges (1995) three-parameter model that provides greater power and can be interpreted as a more direct test of publication bias (Rodgers & Pustejovsky, 2020). This model was fit to all published effect sizes, using a one-sided cut-off parameter at $p < .05$, assuming greater effect sizes for published effects. The selection model including an additional parameter did not yield a better fit than a model assuming no

⁸ This analysis deviated from the original preregistration based on helpful reviewer suggestions.

publication bias ($\chi^2 = 0.38, p = .54$); thus, the Vevea and Hedges method does not yield evidence of publication bias.

To complement these traditional tests of publication bias, we evaluated whether publication status moderated the overall effect size of peer observation on decisions to take risks. Of the 53 reports included in the meta-analysis, 40 were classified as published and 13 were classified as unpublished. Results indicated that effect sizes derived from published work were significantly larger than effect sizes derived from unpublished work (Hedges' $g = -0.17, p = .020$, 95% CI $[-0.30, -0.03]$; Supplemental Figure 4b). Running this model using the narrow age criterion yielded a nonsignificant result (Hedges' $g = -0.11, p = .18$, 95% CI $[-0.28, 0.06]$). Thus, the analysis of publication status as a moderator revealed mixed evidence that depended on the age sample used.

Taken together, though not entirely conclusive, the overall balance of evidence does not support the presence of significant publication bias in the reported results.

Discussion

Public health statistics reveal that adolescents are more likely to take risks when they are in the company of peers. The body of experimental psychology research that has amassed over the last decade investigating this "peer effect," with a wide range of experimental designs and manipulations, has revealed a more nuanced and complicated landscape that consists of results that both support and fail to find evidence for this effect. In the present meta-analysis, we undertook a systematic examination of the effect size and specificity of adolescent decisions to take risks when under the watchful eye of their peers. Additional analyses targeting key theoretically driven moderators were conducted to identify what aspects of decision contexts and what qualities of peers and peer contexts influence adolescents' decisions about risk.

Across 53 reports of 62 studies, 186 effect sizes, and over 5,000 participants, we found evidence that being observed by peers increases decisions to take risks during adolescence with a small effect size, relative to decisions to take risks alone (Figure 3). Importantly, this overall effect was qualified by moderation by peers' expression of their own risk preferences. Moderator analyses revealed that the effect of peer observation increased to medium in size when peer observers were expressing pro-risk attitudes, whereas conditions involving the mere presence of peers without pro-risk messages yielded a negligible effect size when tested on their own (Figure 5f). Collectively, these results tentatively suggest that the mere presence of peers may not be sufficient to drive up risky behavior in adolescence meaningfully, unless the accompanying peers are also expressing pro-risk attitudes. Moreover, the range of experimental approaches taken by scientists to study this phenomenon, while laudable, may have challenged a clear understanding of key factors that moderate the size of this effect. Below, we interpret the observed results and offer suggestions for future work in this area.

Effect of Peers on Adolescent Risky Decisions

Synthesizing across different experimental contexts and peer manipulations, we found that peer presence plus risk-related messaging exerts differential impact on adolescent risky choices. Pro-risk messaging increased the effect of peer observation on risky

choices (Figure 5f). These effects become more practically interpretable when translated to odds ratios. Adolescents are 2.52 times as likely to take a risk when pro-risk peers are observing relative to when they are not, 1.13 times as likely to take a risk when peers are observing choices and not expressing risk preferences, and 1.07 as likely to take a risk when peers express antirisk preferences. The effect of peer observation is only statistically significant in the pro-risk condition. Yet, we note that this effect should be interpreted with caution because the finding is not significant when using the narrow age criteria described in the Method section.

It is instructive to compare the magnitude of these effect sizes to meta-analyses on similar topics and to general conventions in the field. In a recent meta-analysis investigating shifts in risky decision-making across development, Defoe et al. (2015) found that adolescents and children were reliably more likely to take risks than adults, with an average effect size of Hedges' $g = .37$ for adolescents versus adults. Thus, adolescents' (and children's) tendency to engage in risky decisions relative to adults is a substantially larger difference than the effect peer observation has on adolescents' risky decisions when considering the overall effect of peer observation without factoring in peer risk preferences ($g = .16$). In a broader survey of over 100 years of social psychological research, Richard et al. (2003) compiled results from more than 25,000 studies and found that effect sizes in social psychology average $r = .21$ (equivalent to Cohen's d /Hedges' $g = .43$). The effect of pro-risk peer observation on adolescents' risky decisions is greater than this, whereas the effect of neutral peer observers is not significant and substantially lower in effect size.

Evaluation of Moderators

In addition to evaluating the overall effect size of the influence of peer observation on adolescents' risky decisions, we examined a range of moderating factors that could systematically strengthen, attenuate, or reverse this effect. We selected aspects of experiments and participant samples including the age of adolescents, aspects of the decision-making measure, and aspects of the peer's involvement proposed by theory and prior research. These analyses largely yielded null or inconclusive effects (Figures 4–5), with the important exception of pro-risk peer attitudes as a significant moderator, as discussed above.

The equivocal nature of many of the moderator results stems from characteristics of the available data. When coding features of the study population, design, and key variables such as "adolescents," "peers," and "risky decisions," we observed tremendous variability in how the field operationalizes these concepts. Moreover, sample sizes were highly variable, ranging from $N = 13$ to $N = 452$ across studies. This variability may have contributed to the equivocal effects by reducing the number of observations available for a given level of a moderator, or generating highly variable psychological conditions that (perhaps) vary in the degree to which they exemplify the core construct.

Age Moderation

The studies included in the present meta-analysis covered a wide variety of age ranges to characterize "adolescents," ranging from constrained age ranges (e.g., 13–17 years) to very wide age ranges that sometimes extended well into the twenties (see Figure 2a). In

addition, several studies described samples of college students as “adolescents.” While there is no clear developmental endpoint to adolescence (e.g., Somerville, 2016), the tendency to describe participant samples in this way contributes to conceptual confusion especially at older ages, as two publications with the same actual age distribution may describe their results as relevant to adolescent or young adult decisions. We aimed to accommodate this inherent variability by conducting analyses with more stringent (narrow) and less stringent (wide) age inclusion criteria, both of which were rooted in the World Health Organization definition of “adolescence” (World Health Organization, n.d.). We urge the field to consider the appropriate age ranges carefully and justify age inclusion criteria with nonarbitrary benchmarks.

In addition to defining what samples qualify as “adolescents” for the overall meta-analysis, we examined moderation of this overall effect by age, as different age groups within the adolescent range have been emphasized as especially prone to peer influence. For example, research has shown that mid-to-late adolescents are especially attuned to peer observation (Somerville et al., 2013), whereas other work has demonstrated that early adolescents endorse the least resistance to peer influence (Sumter et al., 2009). Thus, we included age moderators to evaluate whether peer observation effects were linearly (steadily increasing or decreasing) or quadratically (adolescent-peaking or troughing) moderated by age. The resulting tests of age moderation were not significant (Supplemental Figure 3c–d).

It should be noted, however, that it was necessary to code studies based on the mean age of the *sample as a whole*, as individual datapoints were not available. This results in lost precision as studies with samples of (for instance) 16–17 year old, and 12–20 year olds, could be characterized similarly in this analysis ($M_{\text{age}} \sim 16.5$ years). The inherent limitation produced by summarizing sample ages using the mean may have reduced precision and hence power to detect age differences in the influence of peer observation on risky decision-making in this meta-analysis.

Moderation by Decision Factors and Peer Factors

The present meta-analysis aimed to incorporate research that characterized adolescent risky decision-making under peer observation. As is evident in the pool of studies included, researchers take widely varying approaches to manipulate and measure *risky decision-making*, *peer observation*, and their combination. Generally speaking, this variability should be considered as a sign of robustness—both in this meta-analysis and in the field more generally. Testing a phenomenon using a range of theoretical and methodological perspectives enhances generalizability and avoids reaching conclusions that depend on the idiosyncrasies of any one approach (Baribault et al., 2018).

Researchers take a wide range of methodological approaches when designing tasks to measure risky decision-making in the lab. These methodological choices include whether a concrete outcome related to task performance is at stake (i.e., incentive compatibility), how much information is known about the probability of positive or negative outcomes, how exciting the task is, and whether the presented choice options have the same or different expected values. Though prior work suggests that these factors are theoretically relevant to adolescents’ decisions to engage in risky behavior and potentially, peer influence effects, the results of the meta-analysis did not identify significant moderation by any of these

variables (Figure 4). It is possible that the corpus of studies evinced such a wide range of experimental approaches that it reduced power to detect categorical moderation of individual decision variables.

Psychologists and economists have combined decision and peer variables in different ways to develop tasks to study risk preferences and risky choices in the lab, many of which are represented in this meta-analysis. This has been of tremendous benefit to the field and provided researchers with an array of options to select from when designing experiments. Some tasks are used frequently and have well-characterized measurement properties that have been demonstrated across a range of populations (see Supplemental Table 2). Still, for most tasks, reliability and validity data are limited or not known. Moreover, many lab-based decision tasks are not meaningfully related to real-world risky behavior (Frey et al., 2017; Schonberg et al., 2011).

Several avenues for future work emerge. First, it will be important for the field to continue to make strides towards documenting the predictive power of these laboratory-based assessments towards real-world risk preferences and behaviors (Dahne et al., 2013; Frey et al., 2017). Future work could also aim to compare risky choice behavior under peer observation across types of risk tasks within the same participants to evaluate cross-task consistency or boundary conditions. In the present meta-analysis, we noted that several reports disseminate the results of multiple tasks. Yet, it was not always clear whether performance on these tasks should track in parallel, or whether the different tasks were intended to measure different—but complementary—aspects of cognitive processing or decision-making. A better understanding of the interrelations across tasks could inform decisions of the number and type of tasks to include when designing experiments.

In addition to work that builds on existing tasks, there has been a call to develop new experimental paradigms that “bridge the gap” between cognitive risk models and naturalistic risk-taking behaviors (Frey et al., 2017; Schonberg et al., 2011). These paradigms may benefit from mathematical modeling that isolates specific cognitive features that give rise to complex decisions into component parts, provoke emotional engagement, and predict real-world risk-taking (e.g., Tymula, 2019). In addition, there are important challenges in translating computational decision models developed based on research in adults for use in developmental populations (Hartley & Somerville, 2015; Wilson & Collins, 2019). Undertaking a computational approach with data from youth warrants heightened attention to the reliability and quality of model solutions (e.g., evaluating age variation in model fit and simulation-and-recovery statistics), and to whether the assumptions of underlying cognitive processes inherent within the model translate straightforwardly to developmental populations. When used with care, these approaches may permit stronger links to be drawn between data and the different theoretical mechanisms that may account for peer observation effects (see Recommendation 5 below).

We also observed substantial variability in the nature of peer involvement in the decision-making process. While some experiments incorporated actual peer observers looking over the participant’s shoulder, other studies implemented deceptive or web-based manipulations where peers were supposedly or actually watching the participant’s choices via computer. The test for moderation by in-person peer involvement was not significant; that is, conducting studies of peer observation online resulted in a similar distribution of effect sizes. Practically speaking, this result may usefully suggest

that lower burden experimental setups (e.g., online peers) are reasonable design choices that could increase the feasibility of testing large, well-powered samples. We encourage future work in this area to actively adopt a framework for whether experimental control or more naturalistic peer interactions should be prioritized for research questions about the nature and mechanisms of peer influence.

A second aspect of peer manipulations with notable variability is the communication of risk preferences by the peer. The test of moderation by this factor showed a significant effect of peers' risk attitudes (comparing no/neutral messaging, pro-risk, and antirisk) on the effect of peer observation. More specifically, pro-risk peers increase the effect of peer observation on risky decision-making with a medium effect size. Still, we note that confidence in this finding should be tempered because in addition to arising from a smaller subsample of studies, the overall test of moderation was not significant within the "narrow" age criteria, defined as the entire sample falling within ages 10–19 years. Most studies in this meta-analysis did not incorporate a manipulation of peer risk attitudes, though our findings revealed its inclusion has a more sizable effect on adolescents' risky choices than mere observation by "neutral" peers.

Following up on this positive finding, we evaluated the effect sizes using the pro-risk manipulation in more depth to (a) identify whether these effect sizes showed qualitative differences in other aspects of the study designs relative to the overall population of effect sizes evaluated in the meta-analysis and (b) characterize the ways in which researchers implemented the pro-risk peer manipulation.

The 45 effect sizes incorporating a pro-risk peer manipulation were generally similar to the overall population of effect sizes. They reflected overall similar publication years, sample sizes, age characteristics, experimental tasks, peer modalities, number of peers, and rates of incentive compatibility. There were also some subtle differences. The studies including pro-risk effect sizes were somewhat more likely to use unknown peers (because many used confederates to implement the pro-risk manipulation) and driving tasks than the overall population of effect sizes.

Researchers used a variety of strategies to ensure peers expressed pro-risk attitudes. Here, we summarize the primary dimensions of variability. For one, some study designs embedded pro-risk attitudes into direct feedback peers expressed about participants' performance on a given task, actively encouraging the decision makers to engage in more frequent risky behaviors. For example, in a driving context peers might explicitly instruct the participant to, "Go faster!" or state that, "It's boring when you go slow" (e.g., Shepherd et al., 2011). When completing the BART task, participants encouraged riskier choices using verbal expression (Wagemaker et al., 2020) such as, "If you stop now you are chicken," (Bexkens et al., 2019; Cavalca et al., 2013) or, "I wonder how big this balloon can get; you should keep pumping it" (McCoy & Natsuaki, 2018).

Other forms of pro-risk messaging communicated the peer's own choice preferences, rather than delivering explicit instructions on how they had prefer the participant to behave. For example, driving-simulation studies used a confederate actor whom the participant witnessed to drive in a risky manner prior to the participant's drive or endorse risky driving prior to the participant's drive, arrive late, wear specific clothing, and/or exhibit an "attitude" toward the experimenter (Ouimet et al., 2013; Simons-Morton et al., 2014;

Sutherland, 2013). In nondriving tasks, the peer would indicate what they would choose if *they* were playing, which skewed toward riskier options (van Hoom et al., 2017; Webber et al., 2017). Still other studies used peers known to the participant, but surreptitiously instructed them to communicate with the participant in a way that would cause them to make riskier choices; successfully doing so would earn them a bonus payout (Reynolds et al., 2014; Thomas & Cauffman, 2018).

We speculate that in real-world settings, it is more common for peers to freely communicate their risk preferences during risky decision-making than is reflected in these studies. The modest (and in this meta-analysis, nonsignificant) impact of highly controlled "neutral" peer observation conditions—where peers are often instructed not to speak—may signal a mismatch between free communication of daily life and controlled communication often seen in "peer" experiments. Using highly controlled peer interaction contexts to study peer effects, which may not be sufficient to evoke peer observation effects, could impede translatability between laboratory and real-world risk-taking tendencies. We encourage future work to focus attention on incorporating pro-risk, neutral, and antirisk messaging manipulations into research on peer effects to further clarify the impact of this facet of peer influence. Moreover, future work could improve translatability by encouraging more ecologically valid, naturalistic social interactions among peers, which could be coded retrospectively for spontaneous pro-risk messaging.

Significant moderation by peer messaging, with substantially larger effects when peers communicate pro-risk preferences, aligns with the *status-seeking* and *homophily* mechanisms described in the Introduction. For instance, having an explicit confirmation that a peer holds pro-risk attitudes could increase confidence that the peer would grant the participant heightened status for engaging in risk. In addition, pro-risk messaging could provide an explicit cue on how to achieve homophily (i.e., sharing in pro-risk attitudes) and provoke risky choices in service of behaving similarly to peers. These results suggest an important direction for future research centered on gaining a deeper understanding of the impact of pro-risk messages conveyed by peers on adolescent risky decisions when under peer observation and the characteristics of these messages that might be especially compelling in elevating risky choice. That we did not observe attenuating moderation of risky choices when peers communicated antirisk messaging may be due the small number of studies that included an antirisk condition (more studies invoked pro-risk messaging compared to antirisk). Another possibility, that could be tested in future work, is that pro-risk and antirisk messages are differentially impactful on adolescent decisions under peer observation.

Finally, we conducted analyses of publication bias, which evaluates whether the effect sizes are larger in studies that are published, relative to those that were unpublished. We made use of multiple, contemporary analyses to evaluate publication bias and although one analysis did find evidence suggesting a significant publication bias, the bulk of evidence favored the null hypothesis leading us to conclude the balance of evidence did not support the presence of significant publication bias. There are several possible reasons for this. For one, it could be that the analyses were not sufficiently sensitive to identify true publication bias, especially given the nested models used. It is also possible that researchers in this area routinely publish both significant and nonsignificant results. Notably, several studies in the meta-analysis report multiple tests of

peer observation effects but under subtly different conditions; these studies frequently report a mixture of significant and nonsignificant findings, which could explain the aggregate lack of support for publication bias.

Limitations

Ecological Validity Considerations

Peer Contexts. While real-world health statistics indicate that peers influence adolescents' risky decisions, the laboratory-based experimental studies summarized here show subtle effects without clear amplifying or attenuating factors. This possible disconnect prompts consideration of whether lab-based experiments are serving as reasonable experimental proxies for the complex ways that peers engage with others' risky decisions in real life.

For example, lab-based experiments largely feature the participant making a series of one-sided choices that are not reciprocated by the peer. In the real-world, decisions are more likely to be interactive and bidirectional, and part of a larger thread of engagement within existing social relationships. Some decisions may hold consequences for the adolescent in terms of social prestige or consequences for the peers. Indeed, prior work has suggested that prosocial motivations to help friends drives engagement in risk among adolescents (Do et al., 2017). While at least one study included in the meta-analysis focused on the role of consequences for friends in shifting baseline preferences for risk (Powers et al., 2018), the short- or long-term consequences of an adolescent's actions and ongoing social exchanges within which the risky choices are situated remain largely absent from lab-based studies involving peer observation manipulations.

Another feature of the social context that surrounds adolescent decisions is the dynamics operating within the peer groups. For example, theoretical accounts of peer influence highlight that selection effects (e.g., the tendency of adolescents to choose to affiliate with peers who hold similar attitudes and beliefs) and socialization effects (e.g., the tendency for beliefs and behaviors to shift into alignment with peers over time) are likely to bear on the decision maker in interesting and complex ways (Prinstein & Dodge, 2008). The majority of studies examined here lacked information about peer relationships leading into the experiment, during the experiment, and after the experiment. Longitudinal work examining risk preference similarity, friendship stability, and change over time could prove valuable to developing insights in the dynamic nature of peer relationships and the influence of those factors on risky decision-making.

When social norms are transmitted in lab-based experiments, there are usually straightforward cues that the peer would prefer the participant to behave in riskier or less risky ways. Our results revealed that social communication of pro-risk attitudes yielded a much larger effect of peer observation than when the expression of pro-risk attitudes was absent from the social context. For example, Simons-Morton and colleagues used peer-aged confederates who presented their own preference to engage in risky driving (Simons-Morton et al., 2014). In another example, Wagemaker et al. (2020) manipulated verbal scripts by peer observers to actively encourage participants to continue pumping the virtual balloon during the BART task. In the real-world, adolescents are likely to receive messages from multiple different constituencies (e.g., peers,

romantic interests, older schoolmates, parents, teachers, etc.) and these messages may conflict with one another. Because the present meta-analysis focused on the role of *peers*, we excluded several effect sizes derived from conditions that included simultaneous messages from a peer and another person; for example, a mother, as in Thomas and Cauffman (2018). It will be worthwhile for future studies to investigate how adolescents resolve and integrate information from different sources into their decisions about risk.

Decision Contexts. In addition to lacking the complexities of real social interactions, lab-based experiments may also fail to capture certain complexities of risky decisions. In the present investigation, we observed that the way risky decision-making was measured across studies was highly variable, ranging from indicators of risky driving to economic judgments in which information about outcomes was fully described. In addition, some studies included in this meta-analysis did not consider whether risks would be advantageous or disadvantageous to an individual's goals. Real-world decisions hold additional complexities, including greater likelihood that actual rewards and probabilities are unknown and lower likelihood of being one-shot in nature. Real-world decisions may also be simultaneously beneficial and costly for different goals. For example, Blakemore and Mills (2014) have argued that certain forms of risky decision-making (e.g., smoking) may be disadvantageous to one goal (e.g., health) but potentially beneficial at another (e.g., social belonging). Much of this complexity is stripped away in current experimental paradigms, but research may approach greater levels of ecological validity if more complex outcomes are considered in future work.

Finally, several recent large-scale investigations of adult participants have cautioned against assuming that task-based measures that capture *risky decisions* predict real-world *health risk behaviors*. There is rich debate on the degree of association between experimentally derived measures of a person's risk preferences and their tendency to take risks in their daily lives (Anderson & Mellor, 2008; Charness et al., 2020; Crosetto & Filippin, 2016; Frey et al., 2017; Verschoor et al., 2016). The studies included in the present meta-analysis often express the assumptions that (a) that risky behavior in the laboratory correlates with risky behavior in the real world, and (b) that laboratory-based susceptibility to peer observation is an indicator of susceptibility to peer influence in the real world. Making careful distinctions between these measures of risk and acquiring within-subject data across these various contexts would permit more comprehensive, accurate understanding of peer influence effects going forward.

Cultural Context

Overall, the research reported in this meta-analysis took place in seven different countries spread across four continents (North America, Europe, Australia, Asia), and included both English-speaking and non-English speaking study populations. All included studies were written in English, which is the predominant language of publishing in this subfield. Nonetheless, introducing an English language requirement could have introduced bias in the present report if (a) research was published in other languages that reported on effects of peer observation in additional cultures and (b) peer observation effects differed cross-culturally. Thus, care should be taken to generalize this research to the cultures examined and to avoid assumptions of universality. Generally, there is a lack of

cultural diversity in research examining adolescent peer influence and insufficient understanding of cross-cultural differences in its expression—a point which we elaborate on below in Recommendations for the Field.

Recommendations for the Field

Here, we offer several considerations for future research to work towards assembling a collective body of research on peer observation effects on adolescent decision-making to yield more clear and translatable conclusions.

Use Consistent Terminology and Methodology

The present meta-analysis identified a wide range of “peer” and “decision” contexts used to evaluate the effects of peer observation during adolescence, which highlights the wide variability in how these constructs are invoked experimentally. This review also underscores the variation present in the field in terms of how constructs central to this area of research are defined and operationalized. Developing and applying commonly agreed upon definitions and methodological approaches can facilitate direct comparisons of results within and across research groups and, ultimately, generate more widely applicable and translatable conclusions.

As a starting point, based on this systematic literature review, we suggest that researchers aim to root specification of appropriate age ranges for *adolescent* participants within the concrete benchmarks provided by the World Health Organization (e.g., 10–19 years, inclusive of boundary ages). We also recommend increasing definitional clarity surrounding the concept of “risky” decision-making, as the term “risk” implies different meanings when viewed through the lens of economics, experimental psychology, and public health (e.g., Holzmeister et al., 2020; Schonberg et al., 2011). At a minimum, researchers should offer clear definitions of the developmental stage under investigation and what they mean by “risk” to make explicit how these constructs are operationalized within the research presented.

Consider Sample Sizes

The present meta-analysis includes research reports covering a wide range of sample sizes, with few studies reporting on very large sample sizes. Studies with larger samples typically offer more certainty about the magnitude of reported effects, and researchers should aim to conduct studies that are well-powered to target key manipulation(s) of interest. For illustration purposes, we conducted a power analysis based on the $g = .16$ effect size of peer observation on risky decision-making derived from this meta-analysis and solved for the required sample size to achieve 80% power. As in other recent meta-analytic work (Kurath & Mata, 2018), we found that the vast majority of studies included in this meta-analysis had smaller sample sizes than what would be needed to achieve 80% power, given the effect size derived from this meta-analysis.⁹

Of course, feasibility and practicality also shape sample size decisions. Within this area of research, adding peers into the experimental context adds an additional layer of challenge to recruitment plans with the potential to increase the target sample size multifold. Based on the results of the power analysis, we suggest that researchers consider all available options of increasing

statistical power. This includes using of highly reliable measures, using within-subjects designs for the peer conditions unless there are specific reasons to believe that within-subject manipulation might compromise the study’s manipulations, and crafting data collection plans that test each individual in a dyad or group to maximize the data acquired per participant recruited (and ensuring statistical analysis approaches appropriately handle multiple sources of non-independence that may follow from a more complex design). Furthermore, it may be valuable for research groups to pool resources and to collect larger samples than an individual research group could do on their own.

All that being said, it is also important to point out that meta-analytically combining the results from many smaller (and likely underpowered) studies will nonetheless in theory lead to a correct estimate of the population effect size. Still, doing so requires overcoming any publication bias present, something that is facilitated by data sharing, ideally in the form of the raw data. This would allow to researchers to conduct a meta-analysis of individual participant data, an approach far more commonly used in the medical and clinical sciences (Driessen et al., 2020; Rogozińska et al., 2017).

Consider the Specificity of Age-Related Effects

Public health policies focused on adolescents generally assume that the risky behaviors expressed by individuals of this age group are unique relative to other developmental stages. Though we coded whether studies statistically compared adolescent samples to other age groups, we lacked sufficient data to conduct a systematic comparison of the effect of peer observation on adolescents’ risky decisions relative to younger or older ages because the vast majority of studies (all but nine) did not directly compare adolescents to any other age group (see e.g., Gardner & Steinberg, 2005; Powers et al., 2018; Somerville et al., 2019; Tymula & Wang, 2021 for exceptions). As a result, the field still lacks certainty regarding whether patterns of peer observation effects shown in the lab are, in fact, adolescent-specific. We suggest that age-related claims can be strengthened by including nonadolescent comparison age groups (e.g., children and/or adults) within the same experiment, to provide a basis for direct tests of age-related similarities and differences.

Expand Considerations of Cultural Diversity

Risky behaviors are a leading public health concern for youth and show similar developmental trajectories across cultures, with an increase in adolescence followed by a decline into adulthood (Duell et al., 2018). Despite these commonalities, some evidence indicates that the expression of risk behaviors and their prevalence during the adolescent years varies across different cultures and societies (Kloep et al., 2009). Thus, whether and how culture and societal traditions

⁹ Results of the power analysis based on the overall effect ($g = 0.16$) indicated that $N = 308$ (two-tailed) total participants are required to achieve 80% power for within-subjects effects, and $N = 615$ (two-tailed) participants per condition are required to achieve 80% power for between-subjects effects. For the pro-risk messaging effect ($g = .52$), $N = 32$ (two-tailed), total participants are required to achieve 80% power for within-subjects effects, and $N = 60$ (two-tailed) participants per condition are required to achieve 80% power for between-subjects effects.

shape the influence that peers have on adolescent risk taking remains an open question.

The present meta-analysis compiles research from four continents and seven countries, including Western and non-Western cultures. Nonetheless, most of the studies were conducted in the United States and Europe. Thus, the geographical scope of research in this area may need to expand to other regions of the world to fruitfully test specific predictions. Recent work by Steinberg, Icenogle, and colleagues have successfully characterized adolescent cognitive control and sensation seeking in a diverse cross-national population, highlighting the potential for other researchers to follow suit and broaden the cultural scope of their research (Icenogle et al., 2017; Steinberg et al., 2018). For cross-cultural investigations, researchers must consider the translatability of measurement tools developed in Western societies to risk-taking contexts in other countries (Kloep et al., 2009). Even if cross-cultural investigations are not feasible, all studies can move towards including robust descriptions of the demographic information of participant samples (e.g., country of data collection, race, ethnicity, economic and sociodemographic variables) consistently and with as much quantitative precision as possible to define the cultural scope of the work.

Acquire Collateral Data to Resolve Competing Mechanistic Explanations for Peer Observation Effects

Though several possible mechanisms have been invoked to explain peer observation effects on adolescent risky decisions (see Introduction), the true mechanisms are likely to be multilayered and complex. Indeed, it is common for research studies in this field to speculate about several possible mechanisms underlying peer observation effects. Yet, studies rarely acquire sufficient collateral data complementing the central task-derived dependent measures of interest to distinguish between competing explanations for these behaviors. Collateral measures exist indexing social motivation, desire for homophily, reward sensitivity, distraction, physiological arousal, peer closeness, cognitive load, physiological arousal, and beliefs about peer attitudes toward risk. If future research routinely acquired one or several of these measures, we believe the field could make strides towards linking the phenomenon of interest with a mechanistic explanation and would advance theoretical development in this research area.

Conclusion

The present meta-analysis evaluated whether peer observation systematically increased adolescents' tendency to engage in risky decisions. Across 186 effect sizes, representing data from 53 distinct research reports and over 5,000 participants, we found evidence that during adolescence, the impact of being observed by peers crucially depends on whether peers are expressing pro-risk messaging; if they are expressing pro-risk messaging, observation yields a medium-sized increase in risky choices and if they are not, their impact is negligible. Other moderator analyses testing key structural and theoretically relevant factors were largely not significant or not conclusive. We synthesize these findings in light of common conceptions about adolescent risk taking and offer a host of suggestions for future research to increase the robustness and conclusiveness of this vibrant research area.

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