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同儕效應如何影響學業表現？教育期望的中介角色

Decomposing Peer Effects on Academic Achievement: The Mediating Role of Educational Expectations

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同儕效應如何影響學業表現？教育期望的中介角色

Decomposing Peer Effects on Academic Achievement: The Mediating Role of Educational Expectations

本論文係王聖夫君（R11325008）在國立臺灣大學社會學系、所完成之碩士學位論文，於民國 114 年 05 月 28 日承下列考試委員審查通過及口試及格，特此證明

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摘要

本研究旨在探討同儕學業表現影響青少年自身學業成就之機制。本研究援引社會比較理論，假設朋友的學業成就會透過形塑青少年自身的教育期望，進而影響其學業成就。然而，既有研究指出此社會影響有可能帶來正向或負向效果：高成就同儕可能正向激勵學生，亦可能因負向比較而使其感到挫折。此外，若要驗證比較假說，必須將其影響與人際溝通的機制加以區分。本研究使用「美國國家青少年至成人健康縱貫研究」（Add Health）之資料，採用因果中介分析（causal mediation analysis）方法，將同儕總效應分解為直接與間接路徑，並檢驗同儕成就與個人教育期望之間的交互作用。研究結果顯示，同儕效應呈現顯著正向影響，而且此效果部分是透過提高青少年的教育期望所中介，此發現支持了正向社會比較假說。此外，分析亦發現負向的交互作用，意指在同儕學業成就較低的環境中，個人抱持高教育期望所帶來的助益更為顯著。本研究結論指出，教育期望是同儕影響的關鍵機制之一，此發現不僅有助於理解網絡效應（network effects），亦能為未來的教育介入措施提供重要參考。

關鍵字：同儕效應、學業成就、教育期望、因果中介分析

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Abstract

This study investigates the mechanisms through which peer academic performance influences adolescents' own academic achievement. Drawing on social comparison theories, it hypothesizes that friends' academic achievement affects adolescents' achievement by shaping their educational expectations. However, prior research suggests that this social influence may operate in either direction: high-achieving peers may positively motivate students or, conversely, discourage them through upward comparison. Moreover, testing the comparison hypothesis requires isolating its pathway from processes of interpersonal communication. Using data from the National Longitudinal Study of Adolescent to Adult Health (Add Health), this study employs causal mediation analysis to decompose the total peer effect into direct and indirect pathways and to assess interaction effects between peer achievement and individual educational expectations. The findings reveal a significant positive peer effect, and this effect is partially mediated by adolescents' educational expectations, supporting the positive social comparison hypothesis. Furthermore,

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the analysis identifies a negative interaction effect, suggesting that the benefits of high educational expectations are more pronounced in low-achieving peer environments. The study concludes that educational expectations represent a critical mechanism of peer influence, offering valuable insights for understanding network effects and informing educational interventions.

Keywords: peer effects, academic achievement, educational expectations, causal mediation analysis

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Chapter 1 Introduction

Does our friends' good academic performance influence our own by motivating us to pursue higher educational achievement? Although a substantial body of evidence demonstrates that adolescents' academic achievement is influenced by their peers (Sacerdote, 2011; Barrios-Fernandez, 2023; Lin, 2010), the mechanisms through which these peer effects operate remain poorly understood. Given the ubiquitous similarity among social ties, social scientists have long been keen to understand how much of this resemblance is causally influenced by the people we interact with. Thus, peer effect research aims to demonstrate that attitudes and behaviors spread through social networks via causal effects. This body of work has generated significant insights across various domains, including health (Smith and Christakis, 2008), criminology (McGloin and Thomas, 2019), and especially, education (Sacerdote, 2011). Due to adolescents' heightened susceptibility to peer influence during formative years and the significant policy implications thereof, educational settings have received considerable scholarly attention and are, therefore, the focus of this study.

Nevertheless, despite the large volume of existing research, the mechanisms through which peer effects operate often remain a "black box." On one hand, peer effect studies frequently fail to connect their empirical findings to established social influence theories or to clearly specify the causal processes that might explain observed peer influences.

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This is exemplified by the "social contagion theory" (Christakis and Fowler, 2010, 2013), where the spread of behaviors or attributes is often described using an epidemiological metaphor, implying an automatic and virus-like transmission among social ties, but leaving the underlying mechanism of contagion opaque.

On the other hand, methodological barriers have constrained researchers' ability to empirically test hypotheses about the underlying mechanisms driving peer effects. Estimating causal peer effects is already methodologically demanding, as it requires isolating social influence from network confounding factors such as selection biases arising from homophily—a primary focus of much prior research. Yet, identifying the mechanisms through which peer effects operate presents an even greater challenge. Tracing these underlying causal processes not only compounds the difficulties of working with network data but also demands more sophisticated causal modeling frameworks. Although recent advances have begun to integrate causal inference methods into the study of social networks (e.g., An et al., 2022; Egami and Tchetgen, 2024; O'Malley et al., 2014; Duxbury, 2024; Keele and Kang, 2022), no studies to date have employed causal mediation analysis to unpack how peer effects unfold through specific mechanisms.

Analyses of the mechanisms behind peer effects are crucial for several reasons. First, they are fundamental for refining and developing more nuanced theoretical models of social capital (Lin, 2002), adolescent socialization process (Guhin et al., 2021), status attainment model (Sewell et al., 1970), innovation diffusion (DiMaggio and Garip, 2011), rise of social inequality (DiMaggio and Garip, 2012), macro political phenomena (DellaPosta et al., 2015), collective behavior (Granovetter, 1978; Wiedermann et al., 2020), and any other theories that treat social interactions and networks as foundational explanatory mechanisms for social phenomena (Erikson and Occhiuto, 2017; DiMaggio and Garip, 2012;

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Hedström and Ylikoski, 2010). Simply documenting the existence and magnitude of peer effects leaves critical theoretical questions unanswered. Unpacking the mechanisms, thus, opens this “black box,” and enables researchers to explore, for instance, how cultural elements are exchanged and dynamically coupled with network structures (Lizardo, 2024) or empirically evaluating competing social influence theories, such as social learning theory, social comparison theory, and social control theory, by assessing whether and how their hypothesized social-psychological mediators operate within peer influence processes.

Second, identifying these underlying pathways is vital for effective policy design and intervention. Knowledge of which specific channels are at work—whether it be an improved learning environment, information transmission, or shifts in social norms—enables the development of more targeted and complementary policy solutions (Barrios-Fernandez, 2023). For instance, understanding why adolescents conform to peers’ risky behaviors can lead to measures targeting the psychological motivations behind such conformity. Furthermore, in many real-world contexts, it is neither feasible nor ethically permissible to manipulate individuals’ social networks by forcibly encouraging new friendships or severing existing ones (e.g., Rohrer et al., 2021). In such situations, understanding which key mediators drive peer effects becomes crucial, as it offers an alternative strategy: to modify these mediating processes in order to enhance positive peer influences or mitigate negative ones. Therefore, without insight into these mechanisms, it is difficult to diagnose why certain interventions might fail or to design more effective strategies for the future.

Third, elucidating the channels through which peer effects operate can help explain the considerable heterogeneity observed in peer effect estimates across different studies. Past research has documented a wide array of peer effect magnitudes, with findings vary-

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ing significantly across different contexts and sometimes presenting conflicting conclusions regarding the direction of these influences (Sacerdote, 2011). Such heterogeneity in effect sizes limits the generalizability of peer effects research and its direct application to policy implementation. As Feld and Zölitz (2017, p. 414) pointed out, this variability may arise because the mechanisms generating peer effects are highly context-specific. For instance, they note that while teacher behavior adjustment can be a significant channel in settings like Kenyan classrooms where students share common educators (Duflo et al., 2011), this mechanism would be irrelevant in contexts where peer groups might not share teachers (Sacerdote, 2001; Carrell et al., 2009). Thus, a more profound understanding of the specific channels driving peer effects in particular settings is essential for interpreting why these effects differ so markedly across various studies. In summary, examining the mechanisms behind peer effects is necessary for both theoretical advance and policy implementation, a point echoed in several recent review articles calling for this research agenda (An et al., 2022; Bramoullé et al., 2020; DiMaggio and Garip, 2012).

In line with the broader effort to open the "black box" of peer influence (Wolske et al., 2020; Zimmerman and Vasquez, 2011; Harris, 2010; Lavy and Schlosser, 2011), I seek to contribute to the peer effects literature by empirically investigating *how* and *why* peers influence adolescents' academic achievement. Specifically, building on social comparison theories, I hypothesize that adolescents adjust their educational expectations by comparing them to their peers' academic performance. These shifts in expectations, in turn, influence their own academic achievement. This mediating role of expectations is a mechanism long recognized within the status attainment model, which indicates that differential social environments, including peer contexts, shape individuals' expectations, thereby influencing their divergent educational outcomes. In addition to the mediating

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pathway, I also examine the interaction effects: the impact of friends' achievement on an individual's own can be muted or amplified by their educational expectations. Together, these two causal processes offer significant insights into the mechanisms underpinning peer effects.

To test the hypothesized mediating and interactive role of educational expectations, I utilize data from the National Longitudinal Study of Adolescent to Adult Health (Add Health), a rich dataset providing information on adolescents' self-nominated friendships, academic achievement, and educational expectations. Methodologically, I employ a recently developed causal mediation analysis (Wodtke and Zhou, 2020; Wodtke et al., 2023) that allows for the decomposition of the total peer effect on academic achievement into an indirect effect operating through educational expectations and a direct effect encompassing all other mechanisms. The framework also facilitates the investigation of interaction effects between peer achievement and an individual's own educational expectations. One key strength of this analytic strategy is its capacity to appropriately account for exposure-induced confounders, thereby permitting clearer isolation of the social comparison mechanism from communication processes. Furthermore, to address homophily biases and shared environmental confounders, I incorporate group fixed-effects, extensive covariate adjustments, the inclusion of lagged outcomes, as well as formal sensitivity analyses to assess the robustness of the findings to potential unobserved confounders.

My analyses reveal a significant positive endogenous peer effect exists: increasing friends' average GPA from the 20th to 80th percentile (2.41 to 3.29 points) corresponds to an approximate 0.19 standard deviation increase in adolescents' own GPA, consistent with the broad body of existing literature on peer effects in academic achievement. Moreover, this peer effect is significantly and positively mediated (accounting for about 8% of the to-

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tal effect) through individuals' educational expectations. The finding lends support to the positive social comparison theory, which postulates that comparing one's achievement to higher-achieving peers can elevate an individual's motivation, thereby fostering improved academic performance. Additionally, the results show an overall negative interaction: the beneficial impact of an adolescent's high educational expectations on their achievement is more pronounced when they are situated within lower-achieving peer contexts. Additional analysis comparing multiple-layered peer groups shows that while broader groups like graduates, coursemates, and clubmates also exert positive effects on academic achievement, these influences, unlike those from close friends, are not mediated by students' educational motivation. This suggests that the comparison process that impacts adolescents' educational motivation is primarily driven by their intimate friends.

The remainder of this thesis proceeds as follows. Chapter 2 reviews prior literature on peer effects on academic achievement and relevant theoretical frameworks, including the mediating role of educational expectations. Chapter 3 introduces the causal mediation analysis employed in this study, and Chapter 4 details the Add Health data and the operationalization. Chapter 5 presents the main decomposition analysis of peer effects through educational expectations. Finally, Chapter 6 discusses the implications of the findings, considers study limitations, and offers concluding remarks.

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Chapter 2 Literature Review

2.1 Peer Effects on Academic Achievement

The enduring question of how individuals' attitudes, behaviors, and social outcomes are shaped by their social surroundings has long been a central concern in sociology. Within this broad inquiry, peer effects refer generally to the processes through which the attributes of individuals change due to social interaction or exposure to the characteristics and actions of others. Thus, peer effects are a particular form of "social influence," one of the most fundamental concepts in sociology. More specifically, within social network analysis (SNA), the studies of peer effects are conceptually located within the "relational" or "connectionist" approach (versus "positional" or "structuralist" approach) to the "network effect" (versus "network formation"), which emphasizes networks as channels through which flows of resources, ideas, emotions, and influences occur due to direct or indirect interactions among actors (An et al., 2022; Emirbayer and Goodwin, 1994; Erikson, 2013; Rawlings et al., 2023).

Peer effects in educational settings have received especially close scrutiny (Sacerdote, 2011), given that many educational policies—including tracking, school desegregation, and voucher programs—are implicitly based on assumptions about how peer environments shape academic outcomes. Additionally, peers play a disproportionately influential

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role in the lives of adolescent students. Adolescence marks a developmental phase characterized by increased frequency of peer interactions, the adoption of new social roles, and a growing reliance on peer feedback for self-evaluation, social belonging, and identity formation (Brechwald and Prinstein, 2011).

Accordingly, since the seminal Coleman Report (1968) highlighted the importance of peers in educational processes, a substantial body of research has investigated and provided robust evidence of the influence of peer environments on adolescents' academic outcomes (for a review, see Sacerdote, 2011; Barrios-Fernandez, 2023). The general consensus is that exposure to high-achieving or socioeconomically advantaged peers has a positive effect on an individual student's educational outcomes. In particular, students' academic achievement, often measured by test scores or GPA in school, is shaped by both the characteristics of the broader peer composition (Hoxby and Weingarth, 2005; Angrist and Lang, 2004; Imberman et al., 2012; Fletcher et al., 2020) as well as those of more intimate, self-selected friends (Bond et al., 2017; Hsieh and Lin, 2017; Lin, 2010; Ryan, 2001). Beyond academic scores, peers also shape students' other important educational outcomes, such as decisions on advanced course-taking (Frank et al., 2008), application to college (Rosenqvist, 2018), and long-run educational attainment and earnings (Carrell et al., 2018; Patacchini et al., 2017).

In particular, I will concentrate on endogenous peer effects on adolescents' academic achievement, measured by Grade Point Average (GPA). First, the decision to focus on academic achievement is justified by its established importance and the robust evidence of peer influence on academic performance, making it a compelling outcome for a mechanism-oriented investigation. Academic achievement is arguably the most widely researched educational outcome in the peer effects literature (Sacerdote, 2011), provid-

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ing a foundation upon which I can build to explore underlying mechanisms more deeply. Additionally, as an important indicator, GPA has been consistently shown to be a key determinant of subsequent educational trajectories, such as college GPA (Betts and Morell, 1999), and long-term labor market outcomes, including earnings and workforce participation (Hansen et al., 2024; Steindórsdóttir et al., 2024).

Furthermore, while some peer effect research examined the influence of both peers' focal outcomes and their background characteristics simultaneously (e.g., Lin, 2010), I focus exclusively on decomposing the *endogenous* peer effects. Manski (1993) defines and distinguishes between two types of peer influences: *exogenous* peer effects (or known as contextual effects), in which an individual's (*ego*'s) outcome is affected by peers' (*alters*') other characteristics, and *endogenous* peer effects, where an individual's outcome depends on the peers' same outcomes.[1] The two peer effects entail different methodological considerations and carry different policy implications. Specifically, endogenous effects would lead to a "social multiplier," an externality whereby interventions that improve outcomes for some individuals will spill over to benefit their peers, and this feedback effect will result in larger aggregate-level impacts, which emphasizes the importance of quantifying this multiplier for effective policy design. This particular form of peer effect, therefore, is the focus of my investigation and decomposition.

Finally, defining who qualifies as a "peer" is important, as prior studies have employed the term to varying levels of social relationships, ranging from one's single best friend to the entire age cohort composition. Indeed, adolescents are embedded within

[1] In the literature on "causal inference with interference," a similar distinction is also made (Ogburn and VanderWeele, 2014; VanderWeele, 2015, p. 441). Specifically, *direct interference* refers to the direct causal effect of one individual's treatment on another individual's outcome, corresponding to exogenous peer effects. On the other hand, *interference by contagion* occurs when one individual's outcome influences the same outcome in another individual, aligning with the concept of endogenous peer effects.

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multifaceted peer group structures, and distinct peer types may exert differential effects through varying mechanisms (Fujiyama et al., 2021; Lee and Lee, 2020; Min et al., 2019; Yuan and Olivos, 2023). The determination of who constitutes a meaningful "reference group" depends on every individual's subjective choices, yet systematically identifying these processes *a priori* is very difficult. In my main analysis, peers are primarily defined as self-selected friends. For most adolescents, intimate friends typically function as the most salient reference group for social comparison due to more frequent interactions, more intensive information exchange, and more immediate feedback (Yuan and Olivos, 2023). Consequently, close friends–as "significant others" with strong socializing influence—are more likely to shape one's socio-psychological motives, making them the most theoretically and empirically relevant peer group for the purposes of this study. Nonetheless, to access the potential influence of broader peer groups, I also examine peers defined by shared club membership, similar course taking, and grade level within the same school as additional analyses in Section 5.4.

Under the specified research focus and building on extensive evidence documenting peer effects on adolescent achievement (Sacerdote, 2011; Barrios-Fernandez, 2023), I expect the following:

HYPOTHESIS 1 (POSITIVE TOTAL EFFECT)**.** *Adolescents' self-nominated friends' GPA positively influences their own GPA, demonstrating a positive endogenous peer effect on academic achievement.*

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2.2 How Do Educational Expectations Mediate Peer Effects on Academic Achievement?

Though peer effects on academic achievement are well-established, their underlying mechanisms are poorly understood. While some influence may be due to behavior imitation, a substantial part of these effects likely involves some intermediate social or psychological processes, with various social influence theories proposing different mechanisms. While some prior peer effect studies have attempted to examine these underlying mechanisms, they have often been constrained by several limitations: some have only proposed theoretical models without rigorous empirical testing (Patacchini et al., 2017), others have employed outdated or inappropriate mediation methodologies (Sunderland et al., 2024; Walters, 2016; Zimmerman and Vasquez, 2011), or they have focused on mechanisms arguably less relevant to sociologists, such as the "class disruption" mechanism (Lavy et al., 2012a; Gong et al., 2021). I address this gap by focusing on educational motivation (aspiration and expectations) as the key mediator. This mechanism, rooted in the Wisconsin status attainment model and theoretically grounded in social comparison theories, provides a framework for understanding the causal processes of peer effects. Using modern causal mediation analysis, I will specifically test if peer effects on academic performance operate through this motivational pathway.

Educational expectations have long been central to research in the sociology of education and social stratification. For example, the Wisconsin Model of Status Attainment emphasized this point by identifying educational aspirations and expectations as key socio-psychological mediators linking family background to future educational and occupational attainment (Sewell et al., 1970; Sewell and Hauser, 1975; Haller and Portes, 1973). Ex-

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pectations matter not only because they affect both short-term behaviors and long-term outcomes, but also because they are deeply shaped by the social context—particularly the behaviors and attitudes of significant others such as parents, teachers, and peers. Several recent studies continue to examine the role educational expectations play in status reproduction and their implications for intergenerational mobility (Bozick et al., 2010; Fishman, 2019, 2022). Therefore, given the longstanding attention this mediator has received in the sociological literature, it provides a useful entry point for decomposing peer effects.

Moreover, educational expectations are not fixed traits; instead, they are especially malleable during adolescence. One experimental study, for instance, demonstrated both the interdependent nature of students' educational decisions and the malleability of expectations (Amador et al., 2022). Such findings point to the potential effectiveness of interventions on students' educational expectations to disrupt "negative" peer effects, which is especially important in contexts where altering friendship structures may be infeasible. In summary, while the goal here is not to replicate the full causal pathway outlined in the Wisconsin Model (from family origins to educational and occupational destinations), I build on and extend this tradition by focusing on one specific causal pathway proposed within the whole model: educational expectations function as key motivational mediators through which peers influence individual academic achievement (Davies and Kandel, 1981; Duncan et al., 1968). Additionally, this allows policymakers to assess whether, and to what extent, interventions aiming to leverage peer effects can do so by targeting adolescents' educational expectations.

Decades of scholarship have separately established (i) that students exposed to higher- versus lower-achieving peers often develop differing educational aspirations or expectations (e.g., Yuan and Olivos, 2023; Rosenqvist, 2018; Borgen et al., 2023; Rosenqvist and

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Brandén, 2024; Lorenz et al., 2020), and (ii) that stronger aspirations or expectations foster higher school performance (e.g., Domina et al., 2011; Dochow and Neumeyer, 2021; Fishman, 2022; Vaisey, 2010). However, these parallel findings do not amount to direct evidence that the educational motivations necessarily *mediate* the peer effect on academic outcomes. In theory, the two causal relationships can operate in entirely different sets of individuals. That is to say, the students whose aspirations rise after exposure to high-achieving peers may not be the same students whose heightened aspirations subsequently improve their academic performance. Hence, it is possible that no single student traverses the full causal pathway from peer academic achievement to motivation to personal academic success, in spite of empirical support for each pairwise relationship. To the best of my knowledge, no prior research has conceptually synthesized these strands of literature into an integrated framework for understanding the peer effects on academic achievement. Nor has any study applied formal mediation analysis to empirically test this hypothesized pathway and to *quantify* the degree to which this specific mechanism accounts for the overall peer effect.

More importantly, existing literature in the sociology of education and social psychology offers two opposing predictions regarding whether exposure to high-achieving peers will *boost* or *depress* students' motivation. While some theories suggest that upward comparisons would serve as a source of inspiration and elevate students' own aspirations, other scholars argue that having high-achieving peers would undermine students' confidence and discourage their educational ambitions. These competing perspectives imply that the mediating role of educational expectations is theoretically ambiguous: it may either amplify or suppress the overall peer effect, depending on the direction of the social

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comparison process.[2]

2.2.1 Negative and Positive Impact of Social Comparison

Based on reference group theory (Kemper, 1968), which posits that individuals use certain groups as standards for self-evaluation and behavior, friends' academic performance is a meaningful point of reference for adolescents, shaping how students perceive and adjust their own educational goals and efforts. Building on this logic, social comparison theory (Festinger, 1954) delves deeper into the psychological mechanisms underlying this evaluative process. It posits that individuals assess their abilities and performance by *comparing* themselves to others' social outcomes, particularly in situations where objective standards are lacking or ambiguous. In academic settings, such comparisons are routine: students often check who received the highest test score, how their grades compare to those of their peers, and so on. However, such social comparison may lead to both positive and negative effects.

Some scholars argue that the social contrast would *lower* students' educational aspirations and expectations. According to "Big-Fish–Little-Pond Effect" (BFLPE), being surrounded by high-achieving peers would undermine individual students' academic self-concept and *lower* their educational motivation. Classic work by Davis (1966) first highlighted this by observing that college students in highly selective academic environments reported lower career ambitions than comparable students in less competitive settings, as they adjusted their aspirations downward due to relative deprivation. Studies by Marsh and colleagues (Marsh, 1987; Marsh and Parker, 1984) further established the BFLPE

[2] A *positive total effect* does not preclude the existence of *negative indirect effect*. Since the total effect aggregates across multiple, potentially opposing mechanisms, the contribution of any one specific mechanism may attenuate the observed overall impact.

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in K-12 settings, finding that attending a school with high average achievement levels tended to lower students' academic self-concepts and educational or career aspirations when compared to equally able students in schools with low average achievement levels.

The negative consequences of upward social comparison have also been documented across various contexts. For example, research on Swedish students has shown that exposure to higher peer average grades within the same school cohort decreased the likelihood of applying to upper-secondary programs (Rosenqvist, 2018). Similarly, Jonsson and Mood (2008) found that Swedish students with high-achieving schoolmates demonstrated a lower propensity to make high-aspiring educational choices, arguing that students assess their probability of succeeding at higher education by comparing their achievements with those of their peers, leading them to adjust their educational ambitions accordingly. In Norway, Borgen et al. (2023) observed that a higher share of girls in lower secondary schools, indicative of a higher average academic achievement level among peers, was associated with reduced student motivation for schoolwork and a lower likelihood of students attending an academic track in upper secondary school. Lastly, Park (2021) suggested that adolescents positioned at the lower end of the school's economic hierarchy lead to one fewer year of education, consistent with the negative social contrast thesis. Notably, He also found that educational expectations mediate over 20 percent of this relative deprivation effect on educational attainment. Overall, these findings demonstrate that students who unfavorably compare themselves to the high achievements of their peers may experience feelings of inadequacy or failure, triggering discouragement rather than inspiration, and fostering a diminished view of their own abilities (i.e., a reduction in academic self-concept), all of which could result in lowered educational aspirations and expectations.

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By contrast, another line of research highlights that exposure to high-achieving peers can significantly *enhance* student motivation and elevate their aspirations. This perspective suggests that individuals do not always react negatively to superior others; instead, they might engage in “positive social comparisons” (Festinger, 1954; Collins, 1996; Buunk et al., 1990; Diel et al., 2024; Suls and Wheeler, 2013). Several reasons can contribute to this positive impact. First, high-achieving peers can foster a culture of achievement within the social circles, where academic success is normalized, valued, and considered “cool,” thereby encouraging members to maintain good standing or avoid displaying lower ability (Bursztyn et al., 2019). Second, such an environment can stimulate healthy or constructive competition, particularly with peers who are perceived as similar (Burleson et al., 2005). In other words, observing friends’ success can boost one’s own motivation to strive harder, engage in self-improvement, and achieve comparable results to their peers. Third, high-achieving peers may also boost a student’s confidence by providing direct academic help (e.g., tutoring) and offering social support (e.g., encouragement), thereby mitigating feelings of academic insecurity and diffidence (Ryan, 2001; Zhu et al., 2025). Consequently, upward social comparison can sometimes be internalized as an inspiring challenge—cultivating an “if they can do it, I can too” mentality—rather than a threat, especially if the student perceives their success as attainable and identifies with these high achievers, manifesting as “basking in reflected glory” (BIRGE) effect (Marsh et al., 2000).

Several empirical studies, especially in the social psychology of education literature, corroborate the motivational advantages of upward social comparison. For example, Huguet et al. (2001) indicated that secondary students often select slightly more successful peers, especially close, same-sex friends with whom they identify, as benchmarks for comparison, a practice linked to enhancements in their own academic achievements. (Suls

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et al., 2002) showed that individuals use social comparison to evaluate abilities and opinions, and when evaluating abilities, they may use a "proxy performer" (an experienced other) to anticipate their own success on unfamiliar tasks. Furthermore, they explained that upward comparison can be self-enhancing if individuals assimilate with the superior other, seeing the potential for their own improvement. Additionally, Yuan and Olivos (2023) found a positive correlation between Chinese students' educational goals and the cognitive abilities of their classmates. One experimental research in virtual classroom settings further demonstrated that adolescents exposed to peers with a growth mindset showed increased identification with higher-performing peers and better learning outcomes, although direct upward social comparison without a growth mindset could lead to discouragement (Sheffler and Cheung, 2024). In short, high-achieving peers can function as a positive influence on a student's educational motivation by creating a culture of achievement, providing encouragement, promoting constructive competition, and modeling success. Therefore, upward comparison would inspire and motivate students who might otherwise aim lower.

In conclusion, whereas there is consistent evidence supporting the positive effect of educational motivation on individuals' own academic achievement, how educational motivation is shaped by peers' academic achievement remains inconclusive. Social comparison theory provides a framework that can explain both positive and negative responses to upward comparisons with high-achieving peers.[3] Specifically, while some scholars argue that exposure to high-achieving friends may depress adolescents' educational expectations, others suggest it may inspire and elevate them. Given the mixed evidence, the mediating effect of educational expectations may operate in either amplifying or suppressing the peer effect, depending on the direction of the social comparison effect. Therefore,

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I formulate two competing hypotheses:

HYPOTHESIS 2a (POSITIVE INDIRECT EFFECT)**.** *Since exposure to higher-achieving friends* ***increases*** *adolescents' educational aspirations and expectations, educational expectations* ***positively*** *mediate the peer effect on academic achievement.*

HYPOTHESIS 2b (NEGATIVE INDIRECT EFFECT)**.** *Since exposure to higher-achieving friends* ***decreases*** *adolescents' educational aspirations and expectations, educational expectations* ***negatively*** *mediate the peer effect on academic achievement.*

2.2.2 Social Comparison or Communication?

While social comparison theory illuminates how peers' academic performance can shape—either positively or negatively—adolescents' educational motivation, there is an alternative mechanism driving the process: interpersonal communication. At its core, social comparison theory centers on how individuals *observe* others' behaviors and use these observations as a reference point for evaluating themselves, which can, in turn, influence their attitudes and aspirations. In reality, however, adolescents do not only observe and compare academic outcomes—they also directly communicate their educational expectations with peers, so they may adjust their own plans in response to their friends' stated intentions. In other words, educational expectations are often explicitly stated, discussed, negotiated, and reinforced through conversation, creating channels of social influence rooted in persuasion and conformity.[4] Therefore, to test the social comparison

[3] While it is certainly true that there is some inter- and intra-individual heterogeneity with regards to the social comparison effect (e.g., Skov, 2022; Mussweiler, 2003); that is, different people at different time points may be sometimes motivated and sometimes discouraged by higher-achieving peers, but the overall goal here is not to estimate the causal effects on *individual* level but the overall direction of *aggregate* effects at the population level.

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hypotheses, it becomes crucial to isolate them from the mechanism through interpersonally communicated educational expectations among friends.

In essence, the question of whether students' educational motivations are primarily shaped by comparing to peers' achievements or through interpersonal communication with high-achieving friends reflects a longstanding debate in social network research: *social cohesion* versus *structural equivalence* as competing mechanisms of social influence (Berten and Van Rossem, 2011; Leenders, 2002; Marsden and Friedkin, 1993; Rosenqvist, 2018). In their classic study on the diffusion of medical innovations, Coleman et al. (1957) attributed behavioral contagion to interpersonal communication within physicians' tightly knit community. However, Burt's influential reanalysis (1987) challenged this interpretation, proposing that diffusion occurred through structural equivalence instead—that is, through comparison and competition among actors sharing identical ties, regardless of whether they were directly connected. Subsequent research by Strang and Tuma (1993), using the same dataset, showed that both mechanisms can operate simultaneously. Even though cohesion and structural equivalence are conceptually distinct, in practice, the two mechanisms are often deeply intertwined. For any given individual, cohesive and structurally equivalent ties may mostly coincide, meaning that actors can be both friends and competitors. Therefore, two directly connected actors (i.e., friendship dyads) can influ-

[4]For example, when high-achieving peers share their ambitions through explicit discussions about college plans through subtle gossip about others' academic efforts (Eder and Enke, 1991), students may internalize the belief that similarly ambitious expectations are desirable. In addition, adolescents iteratively adjust their own educational expectations in response to perceived peer norms, forming a weighted combination of others' views. The alignment helps adolescents foster a sense of belonging, gain social approval, and avoid social isolation (Baumeister and Leary, 2017; Goodenow, 1993). Conceptually, these dynamics reflect the general theory of *normative* function of reference groups (Kelley et al., 1952), DeGroot's consensus model (1974), and Carlyle's constructural model (1991), all of which suggest that frequent interaction and the repeated exchange and averaging of peers' expectations (as a form of knowledge sharing) lead the group toward a shared norm, and individual members within the group tend to align with these emergent group values. Several empirical studies also support this view, showing that adolescents' educational expectations and aspirations are significantly shaped by those of their peers (Rosenqvist, 2018; Kretschmer and Roth, 2021; Vit et al., 2024; Raabe and Wölfer, 2019; Carolan, 2018).

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ence one another through both communication *and* comparison, making it empirically difficult to disentangle the two mechanisms (Leenders, 2002, p.10).

In my case, these two distinct pathways should be both taken into account to examine the mediating role of educational expectations in peer influence processes. The first is the direct influence of friends' academic achievement on adolescents' expectations via social comparison, which may either bolster or discourage students' motivation. This view aligns with Burt's (1987) concept of structural equivalence, which posits that social influence and behavioral contagion are driven by comparison and competition among actors occupying similar network positions.[5] The second pathway operates indirectly, through the interpersonal transmission of educational expectations within friendship networks via communication, persuasion, group norms, and conformity pressures. Since my analysis focuses on the social comparison mechanism and tests whether this mediating process is positive or negative, I treat the cohesion-based influence as a confounding pathway (specifically, a treatment-induced confounder) and utilize specialized causal mediation methods to isolate the social comparison effect.

2.3 The Interaction of Peer Context and Educational Motivation in Shaping Academic Achievement

Adolescents' educational motivation not only mediates the effect of peer achievement on their own academic outcomes but also interacts with peer achievement to shape

[5] In Burt's original formulation, structural equivalence refers to actors occupying similar network positions, typically measured by having similar ties to others. He also argued that social influence among such actors occurs mainly through observation, comparison, and competition. In this study, however, I do not compare friends with structurally equivalent non-friends. Rather, acknowledging that close friends are often structurally equivalent, I contend that peer influence within friendships inevitably involves both communication and comparison. Accordingly, my aim is to disentangle these two social influence mechanisms among friendship ties.

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those outcomes. Examining interaction effects is also highly informative for mechanism-based explanations. Whereas *mediation* analysis helps identify how a cause leads to an outcome through intermediate variables, *interaction* analysis reveals when or for whom the effect occurs by identifying the conditions under which mechanisms operate. This sheds further light on causal pathways by highlighting the joint presence of factors necessary for an outcome to emerge (VanderWeele, 2015). In fact, the overall total effect can be decomposed into both mediation and interaction components using the unified framework introduced in the Methods section below.

Although interaction effects have received less attention in prior studies, I argue that there should be a potential *negative* interaction between personal motivation and peer influence. Specifically, when students are embedded in high-achieving peer groups, the positive effect of their own high educational expectations on academic achievement may be diminished or attenuated (Ryan, 2001). This is because students with strong aspirations and high internal motivation may be less reliant on their peers; their goals and ambitions already serve as the primary drivers of performance (Eccles and Wigfield, 2002). This aligns with findings indicating that peer influence is weaker among individuals who already possess strong pre-existing beliefs or attitudes (Wolske et al., 2020). In the current context, highly self-motivated students may be less responsive to their peer environment because their academic trajectory is already strongly shaped by internal goals—which is usually associated with higher socioeconomic status (Vaisey, 2010). Therefore, peer context and individual expectations may act as partial substitutes, and the influence of one reduces the explanatory power of the other in predicting achievement.

In contrast, the positive relationship between an individual's educational expectations and their academic achievement may be particularly strong and crucial for students situ-

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ated within low-achieving peer networks. For these adolescents, who cannot simply "go with the flow" to achieve academic success, personal educational ideals and motivation become critically important for overcoming the inertia or potentially negative influences of their surrounding social environment (Vaisey, 2010). In such contexts, high educational expectations can serve as a vital psychological resource, acting as a *buffer* against the demotivating or less academically oriented influences of a low-achieving peer group. These students must rely more heavily on their own motivation and long-term goals to stay on track and invest sustained effort in their academic journeys.

In summary, high educational aspirations and expectations are not only predictive of success but may demonstrate their most significant impact in environments where peer-derived academic support or normative pressure is weak or absent. This underscores how individual agency emerges from the complex interplay between social structure (networks) and personal values and motives (culture) (Emirbayer and Goodwin, 1994). Accordingly, I propose the following hypothesis:

HYPOTHESIS 3 (NEGATIVE INTERACTION EFFECT)**.** *The positive peer effects of friends' achievement are **weaker** among adolescents with higher educational expectations; conversely, the positive effects of adolescents' educational expectations on achievement are **stronger** among those exposed to lower-achieving peer environments.*

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Chapter 3 Methods

3.1 Graphical Causal Model

To investigate the mediating role of an individual's educational motivation in the transmission of academic achievement among friends, I employ the mediation analysis methods developed in modern causal inference literature (VanderWeele, 2014; Wodtke and Zhou, 2020; Wodtke et al., 2023). Recognizing that peer effects and their decomposition are inherently *causal* estimands, rather than descriptive measures, the analysis necessitates the application of counterfactual reasoning and the explicit articulation of identification assumptions, as outlined by Lundberg et al. (2021). A directed acyclic graph (DAG) in Figure 3.1 illustrates the hypothesized causal relationships between key variables. In this graph, the exposure variable (average peer academic achievement) is denoted as A, the outcome variable (adolescent's academic achievement) is denoted as Y, and the mediator (adolescent's educational aspiration and expectations) is denoted as M.

Furthermore, in modeling this mediation process, two types of confounding variables warrant consideration. First, baseline confounders, collectively denoted as C, comprise all pre-exposure characteristics (observed or unobserved) that may affect the exposure, the mediator, and the outcome. These variables include, but are not limited to, demographic attributes, family socio-economic background, and school context. In the current con-

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text of network analysis, C also includes network confounding, which refers to observed or unobserved factors influencing the homophilous formation of peer relationships and consequently leading to "spurious" similarities in outcomes among friends. (Shalizi and Thomas, 2011).

Second, exposure-induced confounders, denoted as Z, are variables that confound the mediator-outcome relationship and are themselves influenced by the exposure. The exposure-induced confounder in this study is friends' educational expectations. The social cohesion argument suggests that friends' expectations (Z) can shape other individuals' educational expectations (M) through interpersonal communication, persuasion, and norm-setting. Additionally, friends' expectations can indirectly influence other individuals' academic achievement (Y) through externalities such as the classroom environment or changes in teaching methods. At the same time, friends' expectations are shaped by their prior academic performance (A). Accordingly, friends' educational expectations function as such an exposure-induced confounder for the M−Y relationship.

Figure 3.1 also delineates the causal effects under investigation. First, peer academic achievement is posited to indirectly affect an adolescent's academic achievement by shaping their educational motivation ($A \to M \to Y$), consistent with social comparison theories. The model also accommodates the possibility that peer educational motivation is an intermediate step in this process ($A \to Z \to M \to Y$), aligning with the social cohesion perspective, which emphasizes communication and normative influence. since the focus of this study is to test the social comparison hypothesis, the $A \to Z \to M \to Y$ pathway is treated as a confounding path that must be adjusted for to isolate the $A \to M \to Y$ mechanism.

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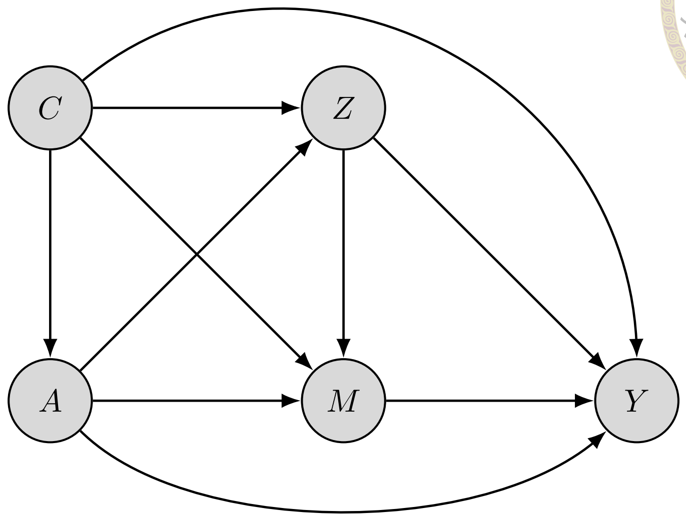

Figure 3.1. Directed acyclic graph (DAG) representing the causal models
Note: C = baseline confounders; A = peers' academic achievement; M = respondents' educational aspirations/expectations; Z = peers' educational aspirations/expectations; Y = respondents' academic achievement.

Second, all the other mechanisms not through the educational motivation are captured by the direct effect ($A \rightarrow Y$), including behavioral imitation and class disruption mechanisms. Third, the graph inherently allows for the examination of interactive effects between the exposure A and the mediator M because both variables have a causal arrow pointing to the outcome Y (VanderWeele, 2009). Therefore, the impact of peer academic achievement on adolescent achievement could vary depending on the adolescent's level of educational motivation.

These mediation and interaction effects are what I aim to identify. However, as demonstrated in Figure 3.1, confounding factors C introduce bias into the $A{-}M$, $A{-}Y$, and $M{-}Y$ relationships, so the mediated and interactive effects cannot be consistently estimated if C is not fully adjusted. An even more problematic issue is the presence of the exposure-induced confounder Z, which both confounds the $M{-}Y$ relationship and is also affected by A. The causal mediation literature has shown that traditional medi-

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ation estimands—the natural direct effect (NDE) and the natural indirect effect (NIE) —cannot be identified when exposure-induced confounders exist, even when they are observable (Robins and Greenland, 1992; VanderWeele et al., 2014; VanderWeele, 2015). This non-identifiability stems from the violation of the "cross-world independence assumption," a strong prerequisite for identifying NDE and NIE, which assumes the *absence* of any exposure-induced confounders. Importantly, even if all such exposure-induced confounders are observed, conventional adjustment methods, such as product and difference methods in path analysis or structural equation modeling (SEM; Baron and Kenny, 1986; Kline, 2023), still prove inadequate.[1] Therefore, alternative estimands and special estimation strategies are required when Z is present in the causal model.

3.2 Estimands

To decompose the peer effect, I deploy the causal mediation methods developed by VanderWeele (2014); Wodtke and Zhou (2020); Wodtke et al. (2023). Following potential outcomes notation and the counterfactual framework (Rubin, 1974), I define Y_a as the potential outcome of the academic achievement an adolescent would attain if their friends exhibited achievement level a, and M_a denotes the adolescent's educational motivation under such peer influence. Furthermore, let Y_{am} denote the outcome value that would have occurred if an individual had been exposed to the exposure levels and mediator values under a and m. The last counterfactual definition is $M^R_{a|C}$, referring to a randomly selected level of adolescent educational motivation from its distribution under peer achievement

[1]The intuition behind this can be illustrated using the DAG in Figure 3.1: if Z is not adjusted for, then the $M{-}Y$ relationship remains confounded. However, adjusting for Z creates other issues: (i) it would open a spurious path $A \to Z \leftarrow C \to Y$, as Z is a collider on this noncausal path, so conditioning on Z would induce endogenous selection bias (Elwert and Winship, 2014). (ii) Conditioning on Z will also block the causal pathways $A \to Z \to Y$ and $A \to Z \to M \to Y$.

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a, conditional on baseline confounders C.

With this notation, the "randomized intervention analogue of the average total effect" can be defined as:

$$\text{RATE} = \mathbb{E}\left[Y_{a^*M^R_{a^*|C}} - Y_{aM^R_{a|C}}\right], \tag{3.1}$$

which captures the overall expected difference in an adolescent's academic achievement when peer academic achievement changes from level a to a^*, with the adolescent's educational motivation drawn from its conditional distribution under each of these exposures. This estimand resembles the average total effect (ATE) in that it involves a contrast between two levels of the exposure. However, it entails a randomized intervention on the mediator, rather than relying on the values of the mediator that would naturally occur under different peer contexts. Moreover, if a^* and a are set to represent the academic performance of high-achieving and low-achieving peers respectively (i.e., $a^* > a$), then the RATE is expected to be greater than zero if peer academic achievement positively influences adolescent academic outcomes; otherwise, the RATE would be less than zero.

First, consider a two-way decomposition of RATE as follows:

$$\text{RNDE} = \mathbb{E}\left[Y_{a^*M^R_{a|C}} - Y_{aM^R_{a|C}}\right], \tag{3.2}$$

$$\text{RNIE} = \mathbb{E}\left[Y_{a^*M^R_{a^*|C}} - Y_{a^*M^R_{a|C}}\right], \tag{3.3}$$

$$\text{RATE} = \text{RNDE} + \text{RNIE}. \tag{3.4}$$

The first term, RNDE—short for the *randomized intervention analogue of the natural direct effect*—quantifies how much adolescents' academic achievement is expected to differ between high and low peer-achievement contexts, if all of their own educational motivation were subsequently maintained at a level randomly drawn from the distribution

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of motivation typically observed among adolescents in low-achieving peer groups. Therefore, the RNDE isolates the impact of peer academic achievement on an adolescent's own academic achievement that operates through all potential pathways other than changes in the adolescent's personal educational motivation.

The second term, RNIE—short for the *randomized intervention analogue of the natural indirect effect*—estimates how much their academic achievement differs if their educational motivation are drawn from the distribution typical of this high-achieving peer environment, versus if their aspirations were drawn from the distribution typical of a low-achieving peer environment, all while keeping the exposure to the high-achieving peer group constant for this comparison. It isolates the portion of the peer academic achievement effect that is transmitted through the adolescent's own educational motivation, which is achieved by fixing the peer achievement context (e.g., high peer GPA) and then comparing the outcome under two scenarios for their motivation: one reflecting the motivation distribution of high-peer-achievement contexts and one reflecting the motivation distribution of low-peer-achievement contexts.

The RNDE and RNIE can each be further decomposed into two components, resulting in the following four-way decomposition:

$$\mathrm{CDE} = \mathbb{E}\left[Y_{a^*m} - Y_{am}\right], \tag{3.5}$$

$$\mathrm{RINT}_{\mathrm{ref}} = \mathbb{E}\left[Y_{a^*M^R_{a|C}} - Y_{aM^R_{a|C}}\right] - \mathbb{E}\left[Y_{a^*m} - Y_{am}\right], \tag{3.6}$$

$$\mathrm{RNDE} = \mathrm{CDE} + \mathrm{RINT}_{\mathrm{ref}}; \tag{3.7}$$

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$$\text{RPIE} = \mathbb{E}\left[Y_{aM^R_{a^*|C}} - Y_{aM^R_{a|C}}\right], \tag{3.8}$$

$$\text{RINT}_{\text{med}} = \mathbb{E}\left[Y_{a^*M^R_{a^*|C}} - Y_{aM^R_{a^*|C}}\right] - \mathbb{E}\left[Y_{a^*M^R_{a|C}} - Y_{aM^R_{a|C}}\right], \tag{3.9}$$

$$\text{RNIE} = \text{RPIE} + \text{RINT}_{\text{med}}. \tag{3.10}$$

Therefore,

$$\text{RATE} = \text{RNDE} + \text{RNIE} \tag{3.11}$$

$$= \text{CDE} + \text{RINT}_{\text{ref}} + \text{RPIE} + \text{RINT}_{\text{med}}. \tag{3.12}$$

The first term, CDE, is the *controlled direct effect*, which is the expected difference in an adolescent's academic achievement if they were exposed to a high-achieving peer group versus a low-achieving peer group, under the hypothetical scenario where all adolescents' educational expectations were uniformly set to a specific common level, such as the median value observed in the sample. This estimand, thus, captures the direct impact of peer academic achievement on individual scholastic performance that operates independently of any changes in the adolescents' own educational expectations. It represents the baseline effect of the peer environment when the mediating pathway of individual educational expectations is neutralized by fixing it to a common value.

The third term in the fourfold decomposition, RPIE, is the *randomized intervention analogue of the pure indirect effect*, which captures the contribution of mediation specifically through an adolescent's educational expectations, in the absence of any interaction between the effect of peer achievement and these expectations on the adolescent's own GPA. It estimates the expected difference in an adolescent's academic achievement if they

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were in a low-achieving peer group but their educational expectations were hypothetically shifted to a level randomly drawn from the distribution of expectations found among adolescents in high-achieving peer groups, compared to having expectations typical of their actual low-achieving peer context. This component thus represents the "purest" mediated pathway—how peer academic achievement affects individual achievement solely by altering an adolescent's educational expectations, without this influence being amplified or dampened by an interaction effect.

The remaining two components of the decomposition pertain to interaction effects: one reflects an interaction that operates independently of mediation, while the other captures a joint effect arising from both mediation and interaction. The second term in Equation (3.12), RINT_{ref} or the *reference interaction effect*, represents the portion of the overall effect that is due to an interaction between peer academic achievement and an adolescent's own educational expectations, specifically under conditions where mediation through a change in expectations by peer achievement is not yet considered.[2] This component can be non-zero even if peer academic achievement does not influence the level of adolescents' educational expectations; it purely captures the interactive effect between the peer achievement context and pre-existing expectations, without the mediating process.

The last term, RINT_{med} or *mediated interaction effect*, represents the component of the total effect that arises from both mediation and interaction operating jointly. This occurs if the effect of peer academic achievement on an adolescent's achievement varies depending on the adolescent's level of educational expectations, and critically, these dif-

[2]It can be interpreted in two symmetrical ways. First, it describes how the direct effect of being in a high- versus low-achieving peer group on an adolescent's achievement changes if their educational expectations are those typical of adolescents in low-achieving peer groups, compared to a scenario where their expectations are at a level m. Second, it reflects how the effect of having educational expectations typical of a low-achieving peer group (instead of the value m) on an adolescent's achievement varies depending on whether they are in a high- or low-achieving peer group.

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fering levels of expectations are themselves a result of exposure to different peer achievement contexts.[3] This effect component is non-zero only if peer academic achievement actually influences educational expectations (mediation occurs) *and* the effect of these expectations or peer achievement on the outcome is conditional on the other factor (interaction occurs).

The four basic components provide a foundational framework, as combinations of them can represent various effects discussed in the causal inference literature on mediation and interaction (VanderWeele, 2014, 2015). For example, the sum of two interaction effects constitutes the total effect portion attributable to interaction (PAI). More specifically for the current purpose, the sum of CDE and RINT_{ref} forms the direct effect (RNDE), and the sum of PIE and RINT_{med} comprises the indirect Effect (RNIE). The total effect of peer academic achievement on adolescent achievement is the sum of all four components. In brief, the CDE is the portion of the effect due to neither mediation nor interaction; the RINT_{ref} is the portion due to interaction only; the PIE is the portion due to mediation only; and the RINT_{med} is the portion due to both mediation and interaction operating concurrently.

One point worthy of emphasis is the use of randomized interventional effects. Within this framework, all estimands are defined from an *interventional perspective* (Nguyen et al., 2021), corresponding to hypothetical, yet potentially conceivable, interventions where the mediator is set randomly according to its distribution under certain exposure conditions, rather than individual-specific counterfactual values. This approach has two

[3] It describes how the impact of being in a high- versus low-achieving peer group differs depending on whether adolescents' educational expectations are those typically formed in high-achieving peer groups versus those formed in low-achieving peer groups. Symmetrically, it also shows how the effect of having expectations typical of high- versus low-achieving peer groups differs according to the peer achievement context the adolescent is in.

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main benefits: substantively, these effects are well-suited for answering "what if" questions about the potential outcomes of modifying the exposure or intervening on the mediator. This, in a sense, justifies why we need to decompose peer effects: we can be informed about whether and to what extent a specifically designed policy can enhance positive peer influences or reduce negative ones by altering specific mechanisms. The interaction effects revealed by decomposition also allow policymakers to more effectively target and allocate limited resources toward the groups that are most in need or most responsive. Methodologically, these estimands can be identified under assumptions that are more defensible than those required for traditional effect decompositions, as they remain identifiable even in the presence of exposure-induced confounding.[4]

3.3 Identification Assumptions

The identification of the causal estimands in this study relies on a set of assumptions commonly referred to as the " *conditional sequential ignorability assumption*." These assumptions extend the "conditional ignorability assumption" (Rosenbaum and Rubin, 1983) by requiring that the exposure, mediator, and outcome are each conditionally independent of their respective counterfactuals, given an appropriate set of observed covariates. Specifically, identification requires the absence of unmeasured confounding in the relationships between (i) the exposure and outcome, (ii) the mediator and both the exposure and outcome, and (iii) the exposure and the mediator. These conditions can be

[4] By contrast, traditional estimands of natural (in)direct effects (NDE/NIE) are suited for the *explanatory goal* of decomposing an observed total effect into parts mediated through a specific pathway versus others. However, they rely on conceptualizing hypothetical "in-between" worlds where the mediator is set to a level it would have taken under an alternative exposure condition for each individual. Such conditions are fundamentally unobservable and cannot be realized through feasible interventions. Relatedly, they depend on the strong and usually untenable "cross-world" independence assumption (i.e., $Y_{am} \perp\!\!\!\perp M_{a^*} \mid C$), and the presence of any exposure-induced confounder would violate this).

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formally expressed as:

$$Y_{am} \perp\!\!\!\perp A \mid C; \quad M_a \perp\!\!\!\perp A \mid C; \quad \text{and} \quad Y_{am} \perp\!\!\!\perp M \mid C, A, Z. \tag{3.13}$$

These assumptions require: first, that conditional on a sufficiently rich set of baseline confounders (C), an adolescent's potential academic achievement (Y) is independent of the actual peer academic achievement (A) they are exposed to. Second, conditional on baseline confounders, an adolescent's potential educational motivation (M) must be independent of their actual peer academic achievement exposure. Third, conditional on baseline confounders, observed peer academic achievement, and observed peer educational motivation (Z), an adolescent's potential academic achievement must be independent of their actual observed educational motivation. These assumptions essentially stipulate the absence of unmeasured confounding for the exposure-outcome, exposure-mediator, and mediator-outcome relationships, after conditioning appropriately on observed covariates, including the exposure-induced confounder for the mediator-outcome relationships. Satisfying these assumptions is challenging in observational studies of peer effects.

As for the exposure-outcome relationship, an extensive literature in causal peer effect has pointed out the difficulties in inferring causal impacts based on observed similarities among social ties (for a review, see An et al., 2022; VanderWeele and An, 2013; Bramoullé et al., 2020), including homophily bias, confounding due to shared environment, and the reflection problem. For example, homophily bias arises when individuals select friends who are similar to themselves in ways that also affect the outcome of interest, making it difficult to distinguish selection from influence. For instance, students who are academically successful may be more likely to befriend others with similar attitudes, leading to

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spurious associations between peers' and individuals' academic performance (Flashman, 2012). Consequently, the observed similarity in outcomes may not reflect a true causal peer effect, but rather an artifact of endogenous network formation (Shalizi and Thomas, 2011).

The peer effect literature has proposed several different solutions to address network confounding, such as experimental designs with random assignment of roommates (Guo et al., 2015), instrumental variable approaches (An, 2015; O'Malley et al., 2014), double negative controls (Egami and Tchetgen, 2024), modeling the peer formation process and then using it to statistically correct the peer influence model (Hsieh and Lee, 2016; Hsieh et al., 2020), and Stochastic Actor-Oriented Models (SAOM; Snijders, 2001), to name a few (see Appendix B for a more comprehensive discussion about the difficulties and existing solutions for identifying peer effects). However, a notable limitation of these approaches is their reliance on alternative, sometimes more restrictive, assumptions. Furthermore, their applicability and extension to the mediation analysis remain limited. Consequently, I integrate several regression-based confounding adjustment methods with the aim of minimizing network confounding and satisfying the assumption of conditional sequential ignorability.

First of all, I attempt to mitigate network confounding bias through extensive covariate adjustment, as used in several peer effect studies. These controls are intended to account for the observable homophily selection process (including factors such as race, gender, socio-economic backgrounds, and other most influential factors determining friendship formation) and to address confounding from observable common shocks. As suggested by Boucher and Fortin (2016), conditioning on a sufficiently rich set of observable characteristics may render the impact of latent homophily small.

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Secondly, I incorporate network fixed effects in the model to adjust for observable and, more crucially, unobservable common factors shared by students within the same network. Given that adolescents primarily form friendships within the natural boundary of their school, and that the most common environments shared by pairs of friends are at the school level, I have defined the school as the group. Therefore, this strategy is equivalent to adding school-level fixed effects and can address selection bias arising from the sorting of individuals with similar unobserved characteristics into specific groups, a common strategy used in estimating peer effects (Bramoullé et al., 2009; Hanushek et al., 2003; Sacerdote, 2011; Lin, 2010).

Thirdly, I further control for lagged outcomes by incorporating baseline measures of respondents' academic achievement, which can proxy for unobserved, individual-specific determinants of selection and account for past performance influencing future choices, a technique also noted in the literature for addressing peer selection (Christakis and Fowler, 2007; but see Shalizi and Thomas, 2011). Including these lagged outcomes as control variables amounts to a value-added model that identifies changes in academic performance caused by peer performance.

In terms of addressing concerns about confounders in the exposure- and outcome-mediator relationships, I use the same covariate adjustment methods—conditioning on individuals' and peers' characteristics, school-fixed effects, and lagged self-outcomes—to achieve the unconfoundedness assumption. This approach posits that conditioning on the observed variables is sufficient to account for confounding in the relationship between peers' academic achievement and an adolescent's educational motivation, such that exposure to peers' academic achievement can be viewed 'as if' random, thereby permitting a causal interpretation of the estimated indirect effects. Similarly, this applies to the rela-

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tionship between an adolescent's educational motivation and academic achievement.

One exception is the exposure-induced confounder in the mediator-outcome relationship. To more clearly isolate the explanatory role of an adolescent's own educational expectations in the pathway from peer achievement to their individual academic outcomes, distinguishing it from the communication process, it is crucial to appropriately control for peers' educational expectations. However, conventional adjustment methods fail to achieve this goal, necessitating the specialized estimation techniques known as the Regression−With−Residuals (RWR) method (Wodtke and Zhou, 2020; Wodtke et al., 2023), whose procedure will be described later, to address this thorny issue.

In summary, the combination of the aforementioned identification strategies is expected to substantially mitigate both general confounding bias and confounding concerns specific to social network analysis, such as homophily bias. As highlighted by Wodtke et al.: "analyses of mediation and interaction that adjust not only for individual characteristics at baseline but also for lagged measures of the outcome and postexposure covariates provide some of the strongest protection against confounding bias in observational research" (2023, p. 1494). However, the possibility of unobserved confounding remains despite these adjustments; therefore, as a final safeguard, formal sensitivity analyses will also be conducted to assess the robustness of the estimated total, direct, and indirect peer effects to potential violations of the unconfoundedness assumption by quantifying how strong an unmeasured confounder would need to be to alter the study's conclusions.

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3.4 Estimation

The estimation of the decomposed direct, indirect, and interaction effects will utilize the Regression–With–Residuals (RWR) method (Wodtke and Zhou, 2020; Wodtke et al., 2023). This approach is particularly advantageous as it is designed to handle the complexities introduced by exposure-induced confounders, such as peer educational motivation (Z) in my study. RWR avoids the biases associated with naive adjustment for such confounders (e.g., overcontrol or endogenous selection bias) by residualizing them before inclusion in the outcome model.

The implementation involves fitting a series of models. First, a model for the mediator (M: adolescent educational motivation) conditional on the exposure (A: peer academic achievement) and centered baseline confounders ($C^{\perp}$) is estimated, potentially using a generalized linear model appropriate for the nature of M (e.g., linear or logistic regression):

$$\mathbb{E}(M \mid C, A) = \theta_0 + \theta_1 C^{\perp} + \theta_2 A. \tag{3.14}$$

Second, models are fitted for the exposure-induced confounders (Z: peer educational motivation) conditional on A and C:

$$\mathbb{E}(Z \mid C, A) = \beta_0 + \beta_1 C + \beta_2 A, \tag{3.15}$$

and residuals from this step, $Z^{\perp} = Z - \hat{\mathbb{E}}(Z \mid C, A)$, are computed. Third, a linear model for the outcome (Y: adolescent academic achievement) is estimated, regressing Y on A, M, centered baseline confounders ($C^{\perp}$), and the *residualized* exposure-induced

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confounders ($Z^{\perp}$), including an interaction term between A and M:

$$\mathbb{E}(Y \mid C, A, Z, M) = \lambda_0 + \lambda_1 C^{\perp} + \lambda_2 A + \lambda_3 Z^{\perp} + M(\lambda_4 + \lambda_5 A). \tag{3.16}$$

Finally, the parameter estimates obtained from these models ($\hat{\theta}$s and $\hat{\lambda}$s) are used as inputs into the specific formulas derived for the CDE, $RINT_{\text{ref}}$, RPIE, and $RINT_{\text{med}}$ to compute the decomposed effects (as detailed in the referenced papers).[5] This approach requires the correct specification of the functional forms of these conditional mean models.

In my analysis, results will be presented contrasting adolescents in peer groups at the 80th and 20th percentiles of the peer achievement distribution (i.e., a^* corresponds to the 80th percentile of peer GPA, and a to the 20th percentile). The controlled direct and reference interaction effects are evaluated with educational motivation held constant at the sample median (i.e., m equals the median value of educational aspirations or expectations). Additionally, multiple imputation using 30 replications was used to handle missing data, and standard errors were computed using a non-parametric cluster bootstrap procedure with 500 replications to account for the clustered structure of the data, where respondents are nested within schools. Lastly, all models incorporate Wave II sampling weights from the Add Health study to ensure population representativeness and correct for the survey's complex sampling design.

[5] CDE $= (\lambda_2 + \lambda_5 m)(a^* - a)$; RINT$_{\text{ref}} = \lambda_5(\theta_0 + \theta_2 a - m)(a^* - a)$; RPIE $= \theta_2(\lambda_4 + \lambda_5 a)(a^* - a)$; and RINT$_{\text{med}} = \theta_2 \lambda_5 (a^* - a)^2$.

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Chapter 4 Data and Measures

4.1 Data

To investigate whether peer effects on academic achievement could be explained by changing one's educational motivation, I draw on data from the National Longitudinal Study of Adolescent to Adult Health (Add Health), an ongoing longitudinal study designed to explore the social, behavioral, and biological factors that shape educational and health trajectories from adolescence into adulthood. The Add Health study, with data already collected across five waves, began with a school-based, nationally representative sample of adolescents in grades 7-12 across the United States. The Wave I involved both an in-school survey conducted between September 1994 and April 1995, administering responses from over 90,000 students, and a more detailed in-home interview conducted between April and December 1995 with a subset of 20,745 adolescents. Wave II followed up with many of the original participants (response rate = 88.6%) approximately one year after Wave 1. Throughout these waves, Add Health gathered extensive data on demographic characteristics, family and school context, social networks, and educational outcomes and expectations. The rich information and its panel data design make Add Health particularly well-suited for the current study.

As mentioned earlier, a distinctive feature that sets Add Health apart from other

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datasets is its inclusion of self-nominated friendship information. Specifically, during Wave I in-school questionnaire, adolescents were asked to nominate their five closest male and five closest female friends from the school roster using unique student IDs. Since these nominated friends also completed the in-school survey, researchers can accurately construct peer network characteristics by directly linking respondents to their nominated friends and using the friends' own responses to generate peer-level variables. This approach not only enhances the precision of peer measurement but also allows researchers to treat the school as a natural boundary for constructing complete (sociocentric) social networks with fewer missing link problems.

Furthermore, the availability of information on individual-specific social interactions within each group (where "group" refers to schools in which respondents nominate and interact with each other) allows researchers to apply spatial autoregressive (SAR) models. Rather than relying on *group-level* means of outcomes and characteristics, SAR models let peer measures vary across individuals within the same group. The nonlinearity introduced by variations in the individual-specific social interaction patterns (i.e., peer exposure variables) helps break the linear dependence between endogenous and exogenous peer effects (Lin, 2010), thereby addressing the "reflection problem" (Manski, 1993).

Given these methodological advantages, Add Health has become the predominant dataset in empirical network effect studies across diverse outcomes, including depression (Lee and Lee, 2020), educational attainment (Patacchini et al., 2017), delinquency (Thomas and Marie McGloin, 2013), binge drinking (Guo et al., 2015), substance use (Fujimoto and Valente, 2012), and romantic relationship inauthenticity (Soller, 2015). It has been particularly useful in studies examining the impact of peers on academic achievement (e.g., Hsieh and Lin, 2017; Lin, 2010). Building upon the existing literature, the current

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study further contributes to our understanding by decomposing the well-established peer effect into direct and mediated pathways, thereby providing insights into the mechanisms underpinning peer influence on academic performance.

To construct the analytical sample used in this study, I employed the following sample restriction criteria. Beginning with adolescents who participated in both the Wave I and Wave II in-home surveys ($N = 13,568$), respondents were excluded if they: (1) did not participate in the in-school survey ($n = 976$); (2) lacked information regarding their grade level ($n = 89$); (3) had missing data on the treatment variable—peers' mean GPA ($n = 654$), largely representing isolated respondents without friendship ties; or (4) were missing on the outcome variable—respondents' GPA at Wave II ($n = 760$). Since missingness on mediators and covariates is addressed through multiple imputation, observations with missing data on these variables were not excluded from the analysis. Applying the above exclusion criteria resulted in a final study sample size of $N = 8,788$.

4.2 Measures

Outcome variable - academic achievement. Respondents' overall academic performance is measured using self-reported average grades in four subjects during Wave II. The exact question asked: "At the {most recent grading period/last grading period in the spring}, what was your grade in {mathematics/English or language arts/history or social studies/science}?" These grades, originally reported as letter grades, are converted into a numerical scale (A = 4, B = 3, C = 2, D or lower = 1) to create a continuous measure of academic achievement (grade point average, GPA)

Exposure variable - peers' academic achievement. I construct each student's peer

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network based on the friendship information collected in the in-school survey, where respondents nominated up to five male and five female friends. I define friendships as symmetric, undirected relationships; that is, both out-degree (alters nominated by the ego) and in-degree (alter who nominated the ego) are counted as friendship ties. These adolescents' friendships are their close, ego-centric networks with the most significant and influential peer relationships. Next, the mean academic achievement of peers is calculated based on friends' self-reported GPAs, providing an objective measure of peer influence derived from the peers' actual academic performance, instead of the respondent's perceptions of their friends' attributes.

Mediator variables - educational motivation. I operationalize adolescents' motivation for pursuing post-secondary education using two variables: aspiration and expectation. Conceptually, educational aspirations reflect an individual's goals or desires for future educational attainment, which are often idealized and less constrained by current realities. In contrast, educational expectations represent individuals' assessments of the likelihood that these educational outcomes will actually occur. Thus, expectations are concrete evaluations of the future, typically grounded in present realities. Given this difference, educational expectations may be more strongly influenced by social surroundings, including peers' academic achievement, and may also more directly motivate and shape students' subsequent behaviors.

In Wave I in-home interview, respondents were asked, "On a scale of 1 to 5, where 1 is low and 5 is high, how much do you want to go to college?" This question serves as a measure of respondents' educational aspirations. On the other hand, educational expectations are measured by "On a scale of 1 to 5, where 1 is low and 5 is high, how likely is it that you will go to college?" To assess the mediating roles of the two distinct motivational

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dimensions, I analyze them in separate decomposition models.[1]

Covariates. The control variables encompass a broad range of individual-, family-and peer-level covariates measured from either the Wave 1 in-home or in-school surveys. At the individual level, variables include gender (coded as 1 for female and 0 for male), race/ethnicity (categorized as white, black, Hispanic, or other), immigration status (classified as first, second, or third or higher generation), region (includes West, Midwest, South, Northeast), and school grade (from 7th to 12th grade).

In addition to basic demographic variables, the analysis includes various covariates potentially related to both academic performance and friendship formation processes. Specifically, I control for depression (based on the CES-D, Center for Epidemiologic Studies-Depression, index comprising multiple items related to depressive symptoms); cognitive ability (measured by AHPVT, an age-standardized version of the Peabody Picture Vocabulary Test-Revised); school attachment (averaged over from three Likert-scale Agree-Disagree items: "I feel close to people at this school," "I feel like I am part of this school," and "The teachers at this school treat students fairly"); parental attachment (assessed by averaging responses to two questions: "How close do you feel to your parents?" and "How much do you think your parents care about you?"); autonomy in friendship selection (binary variable based on the question: "Do your parents let you make your own decisions about the people you hang around with?"); number of school clubs respondents participated in; and frequency of skipping school (number of times respondents skipped a full day without an excuse). Furthermore, the baseline value of the outcome variable

[1]Recent methodological developments in causal mediation analysis have extended traditional approaches to the settings in which multiple mediators are of interest, including path-specific and multiple causally non-ordered mediators (Taguri et al., 2018; VanderWeele and Vansteelandt, 2014; Vansteelandt and Daniel, 2017; Zhou, 2022; Zhou and Yamamoto, 2023). However, to avoid additional methodological complexity, I limit the current analysis to single-mediator models, evaluating each motivational variable at a time.

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is included as a crucial control to capture unobserved determinants related to contextual selection, measured as respondents' Wave I in-school GPA percentile rank within their respective school-grade cohort.

Family-level covariates consist of family structure (categorized as living with two biological parents, a stepparent family, a single-mother family, or other family arrangements), parental education (measured by the highest level of education completed by either parent), logged family income, sibship size, and public assistance receipt (yes = 1, no = 0). Four additional network-related covariates are included to capture structural features of social interactions: network size (total number of friendship nominations sent and received), density (based on the union of sent and received friendship ties), Bonacich centrality (indicating the influence of respondents within the sociocentric network), and reachability (maximum number of alters an individual can reach within the whole friendship network).

Peer-level covariates include *friends'* gender, race/ethnicity, immigration status, family structure, mean parental education, and mean educational aspirations and expectations, measured either as percentages or averages. Notably, as peers' educational aspirations and expectations are measured after the exposure variable and are likely affected by it, these two peer variables are treated as exposure-induced mediator-outcome confounders, which necessitates specific methodological handling (i.e., RWR; Wodtke and Zhou, 2020).

Table 4.1 presents descriptive statistics for the study variables. The average GPA of respondents is 2.86 (SD = 0.74), and the average of their peers' mean GPA is 2.87 (SD = 0.51). With regards to the mediators, the mean values for educational aspiration and expectation are 4.55 (SD = 0.9) and 4.27 (SD = 1.03), respectively.

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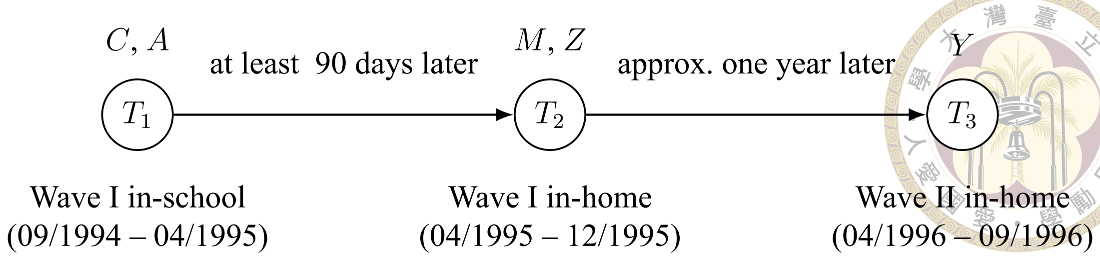

Figure 4.1. Temporal Ordering of Variable Measurements
Note: C = baseline confounders; A = peers' academic achievement; M = respondents' educational aspirations/expectations; Z = peers' educational aspirations/expectations; Y = respondents' academic achievement.

One final note about the methodological strength of using the Add Health is that its panel data design allows us to establish a clear sequential temporal ordering of key variables, which is an essential requirement for the causal mediation analysis (VanderWeele, 2015, p. 25). Figure 4.1 outlines the longitudinal measurement strategy employed to ensure the correct temporal sequencing of exposure, mediator, and outcome variables. More specifically, peer GPA (exposure, A) is measured at Wave I during the in-school survey (September 1994–April 1995). Educational motivation (mediators, M) is then measured at Wave I during the in-home survey, conducted at least 90 days later (April 1995–December 1995). Subsequently, outcome (Y) is the respondent's GPA from the grading period immediately prior to the Wave II in-home survey (April 1996–September 1996). Although educational aspiration and expectations were also measured concurrently during the Wave II survey, this later measure is not used as a mediator This is because the outcome reflects grades already earned *before* the Wave II survey, whereas Wave II educational motivation captures attitudes measured *during* the survey period. Using mediators measured at Wave II would violate the required temporal ordering for mediation (mediator must precede the outcome). Thus, the analysis relies on key variables with a clear sequential structure: $\{A, M, Y\}$.[2]

[2]Replication code for the results is available at https:// github.com/ shengfuw/ Peer-Effects-Decomposition.

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Table 4.1. Descriptive Statistics of the Analytic Sample

Variable	Mean/%	SD	Min	Max
Outcome (Y):				
Overall GPA	2.86	.74	1	4
Exposure (A):				
Peers' mean GPA	2.87	.51	1	4
Mediators (M):				
Educational aspiration	4.55	.90	1	5
Educational expectation	4.27	1.03	1	5
Individual and Family Covariates (C):				
Female	.52	.50	0	1
School grade:				
7	.23	.42		
8	.21	.40		
9	.20	.40		
10	.19	.39		
11	.15	.35		
12	.03	.16		
Race/ethnicity:				
White	.70	.46		
Black	.15	.36		
Hispanic	.10	.29		
Other	.06	.23		
Immigrant generation:				
First	.06	.23		
Second	.07	.25		
Third+	.87	.33		
Family structure:				
Two biological parents	.59	.49		
Stepparent	.16	.37		
Single mother	.19	.39		
Other type	.06	.24		
Region:				
West	.14	.34		
Midwest	.30	.46		
South	.42	.49		
Northeast	.15	.35		
Parental education	13.91	2.40	0	18
Family income (logged)	3.54	.80	0	6.91
Public assistance receipt	.10	.29	0	1
Sibship size	2.52	1.34	1	14

(continued)

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Table 4.1. *(continued)*

Variable	Mean/%	SD	Min	Max
School attachment	3.63	.97	1	5
Parental attachment	4.73	.60	1	5
Allowed to choose own friends	.85	.36	0	1
Depression index	10.41	7.22	0	54
AHPVT score	102.53	13.74	13	139
Baseline GPA percentile rank	57.15	29.38	0	100
Number of club activities	2.46	2.52	0	33
Number of skipped school	.92	4.34	0	99
Number of peers	10.17	5.90	1	39
Network density	.29	.14	0.06	1
Network centrality	.89	.62	0	4.29
Network reachability	5.89	1.22	0	7.49
Peer-Level Covariates (C or Z):				
% female	51.91	27.26	0	100
% white	69.47	37.08	0	100
% black	16.20	31.93	0	100
% Hispanic	11.94	22.92	0	100
% other	7.60	15.28	0	100
% first generation	1.35	8.12	0	100
% second generation	6.67	19.26	0	100
% third + generation	92.41	21.23	0	100
% two-parent family	74.72	23.27	0	100
% single-mother family	21.20	20.95	0	100
% other family type	5.31	11.16	0	100
Mean parental education	14.01	1.51	0	18
Mean educational aspiration	4.55	.68	1	5
Mean educational expectation	4.27	.82	1	5

Note: $N = 8{,}788$. Values are weighted means or percentages, combined across multiple imputed datasets. Data are drawn from Wave I and Wave II of Add Health.

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Chapter 5 Results

5.1 Descriptive Analysis

Figure 5.1 presents bivariate, unadjusted relationships among peer academic performance (exposure), respondents' educational aspirations and expectations (mediators), and their overall GPA (outcome), using spline regression to visualize potential nonlinearities. The left panel illustrates the association between peers' mean GPA in Wave I and respondents' subsequent overall GPA in Wave II. A sharp increase in respondents' GPA is observed when peer mean GPA surpasses approximately 2.0, indicating that exposure to higher-achieving peers corresponds to better academic performance. Additionally, beyond this point, the association appears largely linear, suggesting that a linear functional form is generally appropriate for regression modeling peer influence on academic achievement in this context, particularly for the data segment where peer mean GPA exceeds 2.0.

The middle and right panels of Figure 5.1 explore the relationships between respondents' Wave I educational aspirations and expectations (mediators) and their Wave II overall GPA, respectively. Both mediators exhibit a positive, albeit weaker, association with academic performance. Specifically, higher levels of educational aspiration and expectation are associated with progressively better academic outcomes, particularly at the upper ranges of these mediators. Notably, the slope for educational expectations appears steeper,

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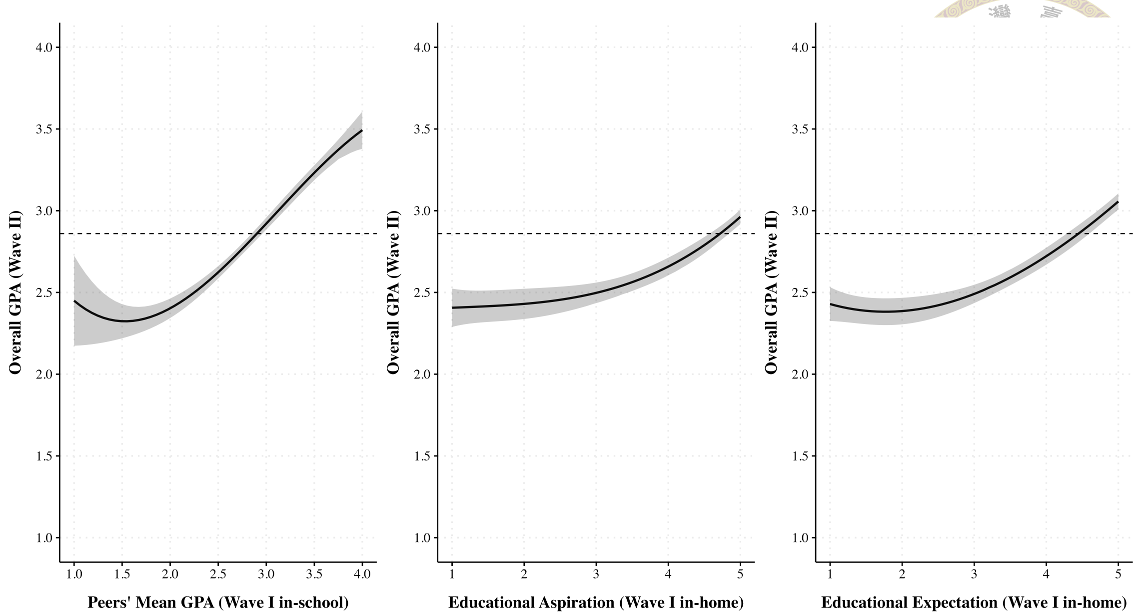

Figure 5.1. Relationships among peers' mean GPA, respondents' educational aspiration and expectation, and respondents' overall GPA

Note: Shaded regions represent 95% confidence intervals. The horizontal dashed line indicates the sample mean GPA.

suggesting it might be a stronger predictor of subsequent academic achievement compared to aspirations.

Figure 5.2 shifts focus to the relationship between peer academic achievement (exposure, measured by quintiles of mean GPA from 1=lowest to 5=highest) and the respondents' educational aspirations and expectations (mediators). Since the presence of differences in the mediator across levels of treatment is one of the necessary conditions for mediation, it is worthwhile to examine the relationship between the two variables.

As for educational aspirations (students' ideal educational goals), the distribution remains relatively stable across different levels of peer GPA. Regardless of peer achievement levels, a majority of respondents consistently report high educational aspirations. In contrast, a clear positive gradient is evident for educational expectations (the realistic assessments of students' likely educational attainment). As peer mean GPA increases across quintiles, the proportion of respondents reporting the highest level of educational

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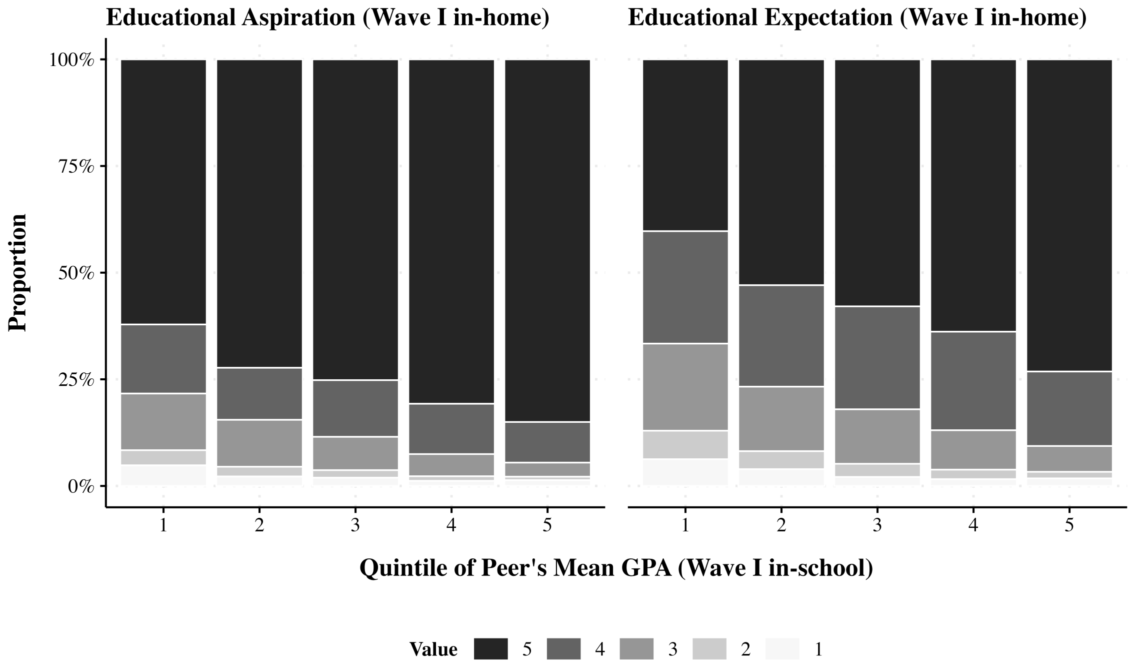

Figure 5.2. Distribution of Educational Aspiration and Expectation by Quintile of Peer Mean GPA

expectations steadily rises. For instance, among respondents whose peers are in the lowest GPA quintile (bottom 20%), fewer than half report the highest educational expectations. This number increases to over two-thirds for respondents whose peers are in the highest GPA quintile (top 20%). This pronounced difference underscores a significant positive correlation between the academic context provided by peers and adolescents' perceptions of their own educational prospects.

Collectively, these initial findings reveal the critical role played by peer contexts in shaping adolescents' academic performance and also point to the potential mediating role of educational expectations. In the following causal mediation analysis, I will formally investigate and decompose these relationships in order to quantify the distinct mediating and interactive effects.

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Table 5.1. Decomposition of the Total Effect of Peers' Mean GPA on Overall GPA into Direct, Indirect, and Interaction Effects

	(1)	(2)	(3)	(4)
ESTIMAND	Educational Aspiration		Educational Expectation	
RATE	.296*** (.024)	.188*** (.026)	.297*** (.024)	.190*** (.026)
RNDE	.286*** (.024)	.178*** (.026)	.285*** (.024)	.175*** (.026)
CDE	.314*** (.026)	.201*** (.028)	.323*** (.026)	.213*** (.029)
$RINT_{ref}$	-.028** (.011)	-.024* (.011)	-.038* (.015)	-.038* (.015)
RNIE	.010* (.004)	.011** (.004)	.012** (.004)	.015** (.005)
RPIE	.004† (.002)	.005* (.003)	.007* (.003)	.009** (.003)
$RINT_{med}$	.005* (.003)	.006† (.003)	.005* (.002)	.006* (.003)
Individual and family covariates	✓	✓	✓	✓
Peer covariates	✓	✓	✓	✓
School fixed effects		✓		✓

Note: $N = 8{,}788$. Estimates are combined across multiple imputation data sets, with the sampling weight applied. SEs are computed using the cluster bootstrap.
†$p < .1$; *$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed tests).

5.2 Peer Effects on Academic Achievement via Educational Expectations: Main Decomposition Analysis

Table 5.1 presents the causal mediation and interaction decomposition of the effect of peer academic performance—measured as the shift from the 20th- to the 80th-percentile of peers' mean GPA during Wave I in-school interview—on adolescents' own overall GPA in Wave II (approximately one year later).[1] Models 1 and 2 consider educational aspirations as the mediator, whereas Models 3 and 4 use educational expectations. To address unob-

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served, time-invariant confounding at the school level, Models 2 and 4 further incorporate school (network) fixed effects. Note that since the outcome variable is standardized, all the coefficients in the tables indicate the extent of increase or decrease in terms of standard deviations.

Across all four specifications, the RATE coefficients (Row 1) indicate a substantial and statistically significant ($p < .001$) total effect: exposure to higher-achieving peers increases respondents' GPA by approximately 0.3 standard deviations in the baseline models and about 0.2 standard deviations when school fixed effects are included (HYPOTHESIS 1 supported). To provide a more straightforward understanding of this effect size, I convert the standardized coefficients back into the original GPA scale. Specifically, when respondents are exposed to high-achieving peers whose mean GPA is at the 80th percentile (3.29 points), compared to those with low-achieving peers at the 20th percentile (2.41 points), their overall GPA will increase by 0.14 points. In other words, each one-unit increase in peers' mean GPA translates into roughly a 0.16-point increase ($\frac{0.14}{3.29-2.41}$) in respondents' own GPA.

The estimated total (endogenous) peer effects align closely with prior research utilizing the Add Health dataset to estimate peer influences on academic achievement (Carbonaro and Workman, 2016; Fujiyama et al., 2021; Hsieh and Lin, 2017; Lin, 2010; Ryabov, 2011). For comparison, Hsieh and Lin (2017) reported endogenous peer effects on GPA between 0.013 and 0.109, varying by the gender composition of friendship pairs, with the strongest impact found among female-female pairs. Differences in effect sizes are anticipated, considering that their model focused on contemporaneous effects, addition-

[1] Appendix Table A.1 and A.2 present selected parameter estimates from the linear regression models fitted for the mediators, the outcome, and the exposure-induced confounders. These coefficients are used to construct the decomposition estimates in Table 5.1, and they are all in the expected directions and of reasonable magnitude.

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ally addressed homophily bias via endogenous network formation modeling, and utilized different sample inclusion criteria and controls. Nevertheless, my findings remain generally consistent with the prior research. While potentially slightly overestimated, the results from the current models, which incorporate comprehensive individual- and peer-level covariates alongside school-by-grade fixed effects to bolster causal interpretation, support the literature. Therefore, the estimates affirm a positive “social multiplier” effect of peer academic performance on individual achievement.

The main contribution of this study is that it moves beyond merely estimating the total peer effect to test hypothesized mechanisms through which peers influence academic achievement: specifically, by changing an individual’s own educational motivations (aspirations and expectations) regarding higher education. Consistent with prior expectations, the decomposition analysis reveals that the pathways operating through these motivational mediators, while not the single or dominant force, are modest yet non-trivial.

Estimates of the RNIE (Row 5) imply that, if respondents were exposed to higher peer mean GPA, an intervention shifting their educational motivation distribution from that typical of lower peer GPA contexts to that typical of higher peer GPA contexts would increase their overall GPA (e.g., by 0.011 standard deviation via aspirations in Model 2, $p < .01$; by 0.015 via expectations in Model 4, $p < .01$). Similarly, the estimates of the RPIE (Row 6), representing the effect of shifting the educational motivation distribution from that typical of low-GPA peers to that typical of high-GPA peers specifically for those respondents situated in a lower peer mean GPA context ($A = a$), are 0.005 for aspirations (Model 2, $p < .05$) and 0.009 for expectations (Model 4, $p < .01$). These indirect effects are consistently positive and reach conventional statistical significance thresholds (HYPOTHESIS 2a supported).

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Accordingly, they provide evidence that the peer effect on academic achievement is partially mediated by influencing one's own educational motivations, with educational expectations appearing as a stronger pathway. More precisely, because these estimands represent *randomized-intervention analogues* of mediation effects, we can infer that for adolescents in lower-achieving peer environments, an intervention designed to shift their educational expectation distribution to resemble that of adolescents in higher-achieving peer groups could effectively improve their academic achievement. Based on the results for educational expectations controlling for school fixed effects (Model 4), such an idealized intervention targeting the mediated pathway specific to educational motivations can eliminate approximately 8 percent (i.e., $\text{RNIE}/\text{RATE} = 0.15/0.19 \approx 0.079$) of the total GPA gap associated with being in low- versus high-performing friendship networks.

However, it must be acknowledged that even after implementing such an intervention on educational expectations, a substantial difference in academic achievement would still remain between those exposed to low-achieving versus high-achieving peer groups. Estimates of the RNDE (Row 2) suggest that exposure to higher peer mean GPA, rather than lower peer mean GPA, would still increase respondents' overall GPA substantially —by 0.175 standard deviation (Model 4, $p < .001$)—even following an intervention that aligned the distribution of educational expectation. Likewise, estimates of the CDE (Row 3) indicate that higher peer mean GPA would increase overall GPA by an even larger margin of 0.213 (Model 4, $p < .001$) after an intervention setting all respondents' educational expectations to a common level (i.e., the median). These direct effects are consistently large, statistically significant, and constitute a major portion of the total peer effect. They likely encompass several mechanisms through which peer achievement might influence individual outcomes, such as behavioral imitation, classroom dynamics and disruption,

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and other cognitive or non-cognitive pathways not operating through changes in adolescents' educational aspirations or expectations.

Additionally, decomposition analyses allow us to examine whether the peer context enhances or diminishes the influence of higher aspirations or expectations on academic performance, and vice versa. The estimated interaction effects here suggest that the interplay between peer academic achievement and individual educational motivations indeed matters. By summing the two components in the fourfold decomposition that involve the interaction, we can assess the Portion Attributable to Interaction (PAI), which represents the total contribution of interaction effects to the total peer influence (VanderWeele, 2014). Calculating the randomized-intervention analogue of this portion (RPAI = $\mathrm{RINT}_{\mathrm{ref}} + \mathrm{RINT}_{\mathrm{med}}$) using Model 4 results for educational expectations yields -0.032. This overall negative interaction suggests that while both high-achieving peers and high individual motivation are beneficial, their combined positive effect is slightly *less* than additive; that is, the positive impact of high motivation is somewhat muted in high-achieving peer contexts. Symmetrically, when students are exposed to low-achieving peer groups, the positive effects of boosting their educational expectations are *stronger* than they are for students in high-achieving peer groups (HYPOTHESIS 3 supported).

In fact, the four-way decomposition provides more fine-grained insights by separating the interaction into two components: the reference interaction ($\mathrm{RINT}_{\mathrm{ref}}$, Row 4) and the mediated interaction ($\mathrm{RINT}_{\mathrm{med}}$, Row 7). From their respective magnitudes, we can observe that the overall negative interaction pattern is primarily driven by $\mathrm{RINT}_{\mathrm{ref}}$, which captures the interactive effect independent of the mediation pathway (i.e., interaction that would exist even if peer GPA did not influence individual motivation). This negative $\mathrm{RINT}_{\mathrm{ref}}$ suggests that the return derived from a high-achieving peer context and the bene-

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fits derived from intrinsic educational expectations (influenced by factors other than peer achievement, like family and school environment) partially overlap or substitute for each other. Consequently, the marginal payoff of having high motivation is slightly *lower* when the peer environment is already advantageous.

On the other hand, RINT_{med}, which captures interaction operating jointly with mediation, is small, positive, and statistically significant ($p < .05$ in Model 4, though sometimes only marginally significant in others). This component reflects the fact that peer GPA does influence motivation, and this peer-influenced motivation, in turn, interacts with the peer context. The positive sign suggests a slight synergistic effect: the specific boost in educational motivation that results from being in a high-achieving peer group tends to produce a slightly larger GPA improvement when the student remains in that same high-achieving context compared to the improvement it would yield in a lower-achieving context. However, this small synergistic effect (RINT_{med}) is considerably smaller than the negative reference interaction (RINT_{ref}), resulting in the overall interaction effects leaning towards substitution or overlapping benefits of the treatment and the mediators.

To summarize, the main findings in Table 5.1—a strong total and direct effect, a modest but non-trivial indirect effect, and some evidence of interaction—offer several insights and compelling support for the mediation and moderation hypotheses. First, peer academic achievement exerts a substantial effect on individuals' own academic performance, aligning with prior evidence on educational peer effects (Sacerdote, 2011). Second, approximately 8% of this total peer effect operates through an indirect pathway: exposure to high-achieving peers elevates individuals' educational expectations, which in turn improves their academic outcomes. The indirect effects are consistent with the positive social comparison perspectives, which argue that higher-achieving peers can inspire

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and motivate other students. Third, while both aspirations and expectations mediate peer effects, educational expectations emerge as the more powerful channel. Fourth, the negative interaction observed between peer academic performance and educational expectations suggests that students with stronger internal motivation benefit slightly less from the additional advantage of high-achieving peers, which indicates that these two positive influences partially substitute for each other. Symmetrically, this implies that interventions aimed at boosting students' educational motivations are likely more important and more effective for those students who are in lower-achieving peer groups. Finally, these results hold even after controlling for extensive covariates and school-by-grade fixed effects, substantially mitigating concerns about network confounding (homophily bias and contextual confounding) and facilitating the causal interpretations. Taken together, the findings sharpen our understanding of the mechanism and interplay between peer contexts and individual motivation and point to concrete avenues for designing more effective educational interventions.

5.3 Sensitivity Analysis

While the inclusion of extensive covariates, school fixed-effects, and lagged outcomes is intended to satisfy the conditional sequential ignorability assumption, the possibility of unobserved confounding in this observational study cannot be entirely dismissed. For instance, latent individual traits such as ambition or unmeasured aspects of family background could influence friendship selection, educational expectations, and academic achievement simultaneously, thereby biasing the estimated effects. To assess the robustness of my findings against such potential biases, I conduct a formal sensitivity analysis developed by Wodtke et al. (2023, p. 1509-1515). This analysis evaluates how the

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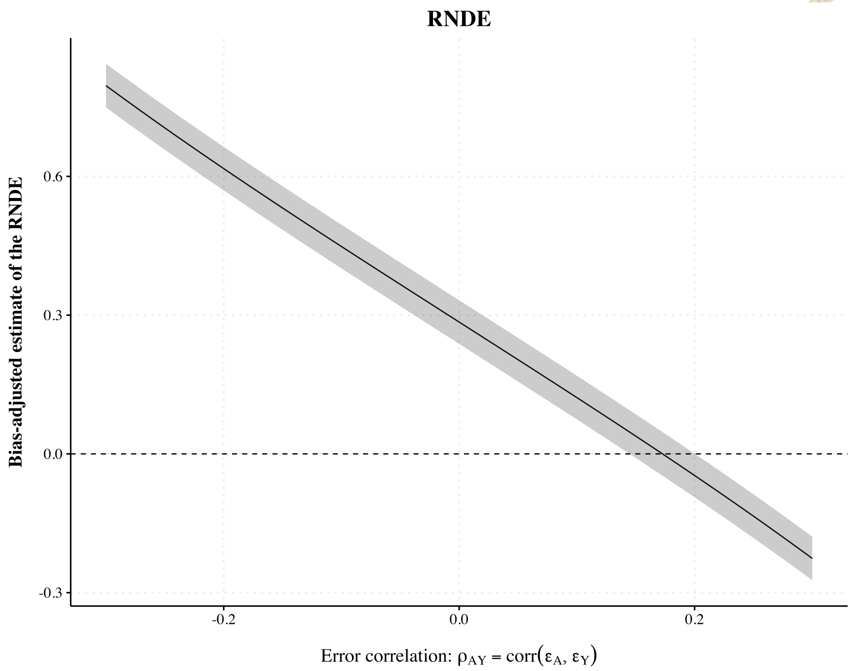

Figure 5.3. Bias-adjusted estimates of the RNDE as a function of the error correlation $\rho_{AY} = \text{corr}(\varepsilon_A, \varepsilon_Y)$.

estimated direct (RNDE) and indirect (RNIE) effects would change under various hypothetical scenarios of unobserved confounding affecting the exposure-outcome (A-Y), mediator-outcome (M-Y), and exposure-mediator (A-M) relationships.

First, I consider the scenario where an unobserved factor confounds the relationship between peer achievement (A) and a student's own achievement (Y). This would occur if, for example, unobserved parental investment positively affects both a student's likelihood of befriending high-achievers and their subsequent academic performance. The correlation between the error terms of the exposure and outcome models, ρ_{AY}, captures the magnitude of such confounding. Figure 5.3 plots the bias-adjusted estimate of the RNDE as a function of this error correlation. A value of $\rho_{AY} > 0$ implies that unobserved factors promoting the exposure to high-achieving peer groups also improve a student's own academic outcomes. As the figure shows, the direct effect of peer achievement remains positive and statistically significant even under a considerable degree of confound-

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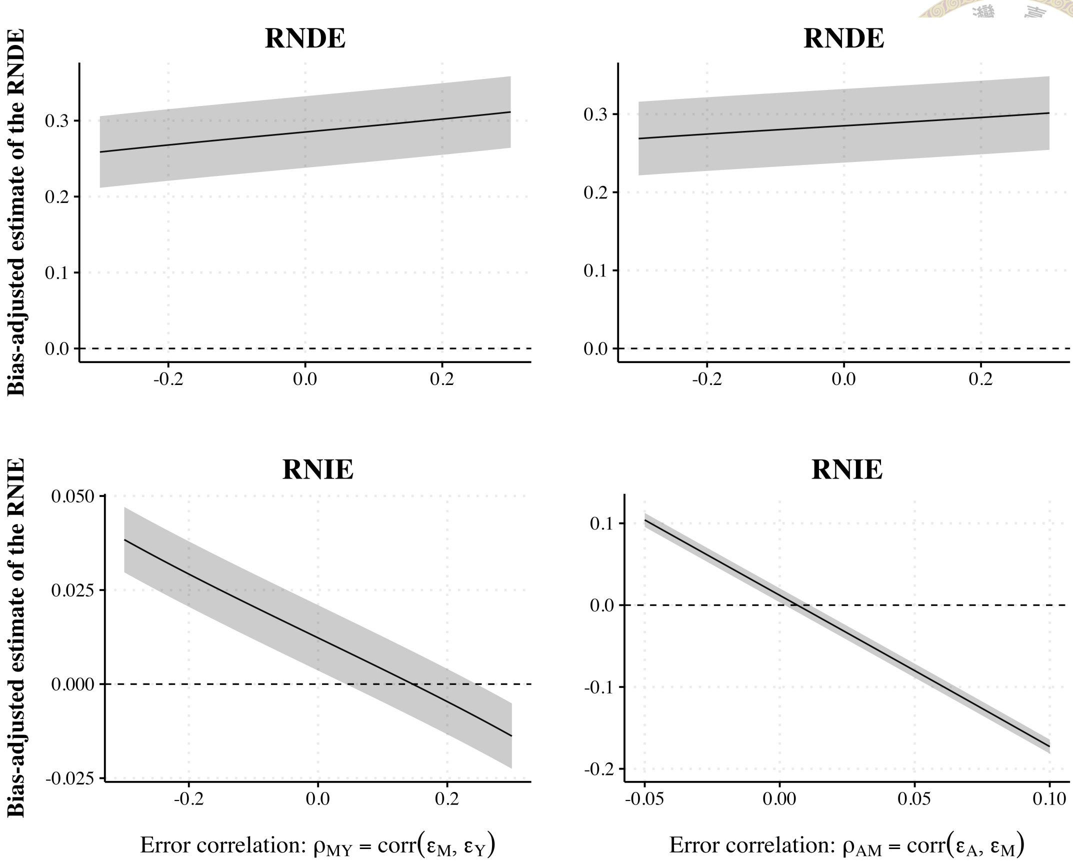

Figure 5.4. Bias-adjusted estimates of the RNDE and RNIE as the functions of the error correlation $\rho_{MY} = \text{corr}(\varepsilon_M, \varepsilon_Y)$ and $\rho_{AM} = \text{corr}(\varepsilon_A, \varepsilon_M)$.

ing. Specifically, peer achievement has a substantial direct effect on a student's own GPA would only be nullified if the error correlation reached approximately 0.2. This suggests that any unobserved confounder would need to be moderately strong to fully explain away the peer effect, lending confidence to the robustness of this primary finding.

Next, I assess the sensitivity of the results to unobserved confounding of the mediator-outcome relationship, represented by the error correlation ρ_{MY}. This type of confounding arises if unmeasured factors, such as a student's intrinsic personality or non-cognitive skills, simultaneously influence their educational expectations (M) and their academic achievement (Y). Figure 5.4 displays the bias-adjusted estimates for the RNDE (top-left panel) and RNIE (bottom-left panel) across a range of values for ρ_{MY}. The analysis reveals two key patterns. First, the estimated direct effect (RNDE) is highly robust; it remains

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substantively large and statistically significant across the entire range of plausible error correlations. Second, the estimated indirect effect (RNIE) is more sensitive. A positive value for ρ_{MY}, which is plausible, would attenuate the estimated RNIE, with the effect reaching zero at an error correlation of about 0.15. This indicates that while the main conclusion regarding the large direct effect of peers is secure against this form of bias, the conclusion about the mediating role of educational expectations is more fragile and should be interpreted with caution.

Finally, I examine the potential for unobserved confounding of the exposure-mediator relationship, where unmeasured factors jointly influence peer achievement (A) and a student's own educational expectations (M). This scenario can happen when students with a latent disposition for high academic goals may be more likely to both select high-achieving friends and form high expectations for themselves. Figure 5.4 also shows the bias-adjusted estimates for the RNDE (top-right panel) and RNIE (bottom-right panel) as a function of this error correlation, ρ_{AM} . The direct effect (RNDE) once again proves to be exceptionally robust to this form of confounding. The indirect effect (RNIE), however, is highly sensitive. The bottom-right panel shows that even a very small positive error correlation would be sufficient to render the indirect effect statistically insignificant. Conversely, a negative correlation—the less plausible scenario—would amplify the estimated indirect effect.

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5.4 To Whom Do We Compare? Effects Across Multilayered Peer Groups

Adolescents are embedded in multiple layers of peer groups, yet prior research on "peer" influence has typically focused on a single level—often emphasizing either school-level peer composition or self-selected friends as the primary source of social influence. However, without knowing which type of peer each individual adolescent actually values and adopts as their salient "reference group," it is more appropriate to examine and compare the influence of multiple peer layers. Only a few previous studies have adopted this approach (e.g., Fujiyama et al., 2021; Lee and Lee, 2020; Min et al., 2019). Accounting for multilayered peer groups is crucial not only because different peer contexts may exert varying degrees of influence, but also because they may operate through distinct mechanisms.

Table 5.2 presents results from a series of models that consider how peer contexts at multiple levels shape adolescents' academic performance indirectly via their educational aspirations and expectations. Peer-level explanatory variables are constructed from distinct peer groupings using data from Add Health. First, grade-level peers are identified by grouping students within the same grade cohorts at their respective schools, capturing institutionally defined peer contexts. Second, coursemates are measured based on the clusters of students with whom they take the course (also known as "local positions;" Frank et al., 2008), derived from high school transcript data respondents provided in Wave III. Third, clubmates are defined using adolescents' self-reported participation in extracurricular activities at Wave I in-school interview, reflecting more voluntary, interest-based peer

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affiliations.[2]

Across all models, the total effects (RATE) indicate substantial and statistically significant impacts. For instance, exposure to higher-achieving grade-level peers raises adolescents' academic outcomes by about 0.25 standard deviations. Coursemates show even larger effects (0.27), while clubmates produce the smallest but still substantial effects (0.18). These findings reaffirm that adolescents' academic trajectories are shaped by the achievement levels of their surrounding peers—ranging from their closest friends to broader, more intermediate peer groups.

However, similar total effects across peer types do not imply that the underlying mechanisms are equivalent. The estimated indirect effects and the interaction effects are consistently negligible and statistically insignificant. These results suggest that the influence of peer academic achievement on students' own academic outcomes operates primarily through direct channels, rather than by altering their aspirations or expectations. Likewise, the interaction effects are close to zero, providing little evidence that broader peer context moderates the impact of one's educational motivation on achievement.

In summary, the findings in Table 5.2 suggest that peer influences from gradesmates, coursemates, and clubmates exert robust, direct effects on academic outcomes. However, these effects do not appear to operate through changes in educational motivation, nor do they systematically amplify or attenuate the effect of adolescents' own expectations on their academic achievement.

[2] One important caveat is that variation in missingness across peer exposure variables results in different sample sizes across models. As a result, comparing the absolute sizes of the estimated coefficients may not be meaningful, though the overall patterns remain informative.

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Table 5.2. Decomposing Peer Effects by Peer Group Type

	(9)	(10)	(11)	(12)	(13)	(14)
ESTIMAND	Educational Aspiration			Educational Expectation		
Exposure:	Grade	Coursemates	Clubmates	Grade	Coursemates	Clubmates
RATE	$.245^{***}$ (.023)	$.274^{***}$ (.034)	$.177^{***}$ (.024)	$.248^{***}$ (.023)	$.272^{***}$ (.034)	$.176^{***}$ (.024)
RNDE	$.245^{***}$ (.023)	$.274^{***}$ (.034)	$.174^{***}$ (.024)	$.251^{***}$ (.023)	$.275^{***}$ (.034)	$.176^{***}$ (.024)
CDE	$.256^{***}$ (.024)	$.289^{***}$ (.036)	$.193^{***}$ (.026)	$.278^{***}$ (.025)	$.300^{***}$ (.038)	$.196^{***}$ (.028)
$\mathrm{RINT}_{\mathrm{ref}}$	-.011 (.009)	-.014 (.016)	$-.019^{*}$ (.009)	$-.027^{*}$ (.013)	-.025 (.020)	-.021 (.014)
RNIE	.000 (.002)	-.001 (.004)	.003 (.003)	-.003 (.003)	-.002 (.006)	.001 (.004)
RPIE	.000 (.002)	.000 (.003)	.002 (.002)	-.002 (.002)	-.002 (.004)	.001 (.003)
$\mathrm{RINT}_{\mathrm{med}}$	.000 (.001)	.000 (.002)	.001 (.001)	-.002 (.001)	-.001 (.002)	.000 (.001)
Individual and family covariates	✓	✓	✓	✓	✓	✓
Peer covariates	✓	✓	✓	✓	✓	✓
School fixed effects						

Note: $N = 9{,}370$ for Grade Peers, 4,135 for Coursemates, and 7,169 for Clubmates. Estimates are combined across multiple imputation datasets, with the sampling weight applied. SEs are computed using the cluster bootstrap.
†$p < .1$; *$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed tests).

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Chapter 6 Discussion and Conclusion

Why do peers affect adolescents' academic achievement? The findings in this study suggest that the peer effect on GPA is partially attributable to students' heightened educational aspirations and expectations. Using data from the National Longitudinal Study of Adolescent to Adult Health and causal mediation analysis within a counterfactual framework, I unveil a key mechanism behind the well-established phenomenon that peers causally influence adolescent academic performance (Bond et al., 2017; Hsieh and Lin, 2017; Ryan, 2001; Lin, 2010). Specifically, I demonstrate that educational expectations both mediate and interact with the effect of self-nominated friends' GPA on an individual's own GPA.

Regarding the total effect of peer academic achievement on adolescents' own achievement, my analyses show that exposing respondents to friends with an average GPA increase from the 20th to the 80th percentile (2.41 to 3.29 points) results in a roughly 0.19 standard deviation increase in their own GPA. This holds true even after accounting for a wide array of individual and contextual covariates, along with school fixed-effects. Furthermore, approximately 8% of this total effect is statistically significantly mediated by changes in the respondent's own educational aspiration and expectations, highlighting the role of internalized motivation as a key cognitive mechanism for peer influence. I also

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find that the peer effect's magnitude varies across individuals with different levels of educational expectation. Specifically, peer academic achievement has a stronger effect on students who hold lower expectations, indicating that goal-oriented motivation moderates susceptibility to peer influence.

These findings generally align with positive social comparison theory. Prior research in sociology of education has debated whether exposure to high-achieving peers motivates or discourages adolescents (e.g., Marsh, 1987; Rosenqvist, 2018; Marsh et al., 2000), and my findings suggest that exposure to high-performing friends appears to foster rather than hinder academic progress. Rather than inducing negative self-evaluation or withdrawal, such exposure generates upward comparison that elevates one's own goals and efforts, ultimately leading to better academic performance. Therefore, education policies that assign or restructure peer groups to increase students' exposure to high-achieving peers can, on average, generate academic benefits. Policymakers should consider how to strategically leverage social comparison to foster constructive competition and enhance overall educational outcomes.

My findings also underscore the importance of how "peers" are defined, as different peer contexts may exert their influences through distinct pathways. By comparing various peer groups—including nominated friends, classmates, clubmates, and the overall grade cohort—I find that only the most intimate peer ties appear to exert their positive influence on academic achievement *through* the motivational channel of educational expectations. This suggests that while more intermediate peer groups do impact academic outcomes, their influence likely transmits via other mechanisms, such as shaping school atmosphere, behavioral imitation, or classroom dynamics, rather than by acting as significant others who strongly socialize individuals' educational values. Conversely, close friends are more

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plausibly the primary reference points for social comparison processes that meaningfully alter educational expectations in a way that impacts academic performance. This may result from the fact that individuals are typically more familiar with their close friends' achievements, share greater similarity with them, and are perhaps more likely to engage in competitions that are both salient and motivationally potent, thereby influencing their own academic effort and performance. I also find that influence on academic achievement through expectations isn't limited to friends at the extremes of the GPA distribution; instead, what matters is the average GPA of friends (see Appendix C). This suggests that adolescents likely compare themselves to the *aggregate* academic level of their entire friend group, rather than being influenced solely by a few "opinion leaders."

My findings make several important empirical contributions to research on peer effects and offer policy implications. First, moving beyond the established existence of peer influence, I empirically unpack the "black box" of these mechanisms by identifying and quantifying the mediating role of adolescents' educational expectations. The findings provide evidence that the total peer effect on academic achievement is transmitted through shifts in individuals' educational expectations, thereby illuminating a specific socio-psychological pathway—positive social comparison—through which peer environments shape individual outcomes. Second, the results highlight the complex interplay between peer context and individual motivation by demonstrating a significant negative interaction effect. The findings indicate that individual educational motivation can serve as a critical buffer or compensatory resource in less academically supportive environments. Finally, these empirical insights suggest that policy interventions fostering positive educational expectations can be highly effective, especially for students in lower-achieving peer groups. For example, policy interventions that equalize educational expectations for two

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students—one with friends in the 20th percentile of GPA and another in the 80th percentile—could reduce their achievement disparities by nearly one-tenth.

Methodologically, I introduce a mediation framework (Wodtke and Zhou, 2020; Wodtke et al., 2023; VanderWeele, 2014) that can be used for future analysis of peer effects in social network analysis. Foremost, it pioneers the application of cutting-edge techniques from causal mediation analysis to the empirical challenge of decomposing endogenous peer effects on academic achievement. A key innovation of this method is its capacity to properly account for exposure-induced confounders. In this instance, it allows for a clearer distinction between mechanisms rooted in social comparison versus those driven by interpersonal communication by disentangling the effect from the pathway that operates through *peers'* educational expectations. Furthermore, the employed decomposition provides a unified structure for estimating not only direct and indirect (mediated) effects but also interaction effects. Lastly, the use of interventional estimands provides estimands with clearer interpretations suitable for policy considerations and is identifiable under more defensible assumptions than the traditional natural (in)direct effect. When combined with rigorous covariate controls, school fixed-effects, and lagged outcomes, this decomposition strategy offers an approach to identify the causal processes underpinning peer influence.

The theoretical implications of my findings also illuminate various subfields within sociology. First, the study refines the classic Wisconsin Model of Status Attainment by empirically elaborating one of its core, yet often broadly specified, mechanisms. I meticulously examine how peer academic achievement shapes adolescent educational expectations and subsequent performance—a socio-psychological process that the Wisconsin Model identifies as fundamental to explaining how students' social background translates into long-term educational and occupational attainment (Sewell and Hauser, 1975; Sewell

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et al., 1970). Future stratification research should better connect these meso- and micro-level processes with analyses of students' SES and their future attainments to fulfill the explanations of intergenerational status transmission.

Second, this study responds to recent scholarly calls to reintegrate the concepts of motives, values, and socialization into contemporary cultural analysis (Vaisey, 2010; Miles, 2015; Guhin et al., 2021). While some cultural sociologists rejected the idea of values and subjective motivations in favor of "toolkit" or "repertoire" metaphors to avoid functionalist pitfalls and concerns about "blaming the victim" (Swidler, 1986; Lamont and Small, 2008), this research demonstrates the explanatory power of educational expectations when conceptualized as salient motives for academic action. More importantly, it illuminates the socialization processes through which these educational motivations are shaped by peer interactions, thereby illustrating how values are not merely abstract ideals but are dynamically formed and reinforced within social networks. In other words, it provides a more holistic understanding of how social context and internalized "conceptions of the desirable" jointly inform conduct and contribute to educational outcomes.

Finally, the study advances social network research by demonstrating that cultural values and motives are integral to network effects. Thus, this challenge purely "structuralist" perspectives that often marginalize the explanatory power of culture, meaning, and subjective motivations (Emirbayer and Goodwin, 1994, p.1413). Aligning with integrative approaches in relational sociology (Fuhse and Mische, 2024; Lizardo, 2024), my findings reveal how cultural factors could explain and modify the network effects. This underscores the necessity of engaging with the "meaning structure" and actors' normative commitments for a more comprehensive understanding of network processes and their outcomes (Emirbayer and Goodwin, 1994; Fuhse, 2009).

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However, several limitations of this study warrant consideration, highlighting important directions for future research. Notably, despite robust methodological efforts to address network confounding, the possibility of unobserved homophily or shared environmental influences persisting in this observational design remains. Future research could try to overcome these issues by adapting sophisticated methods already developed for identifying total peer effects to the mediation settings (An, 2015; O'Malley et al., 2014; Egami and Tchetgen, 2024; Hsieh and Lee, 2016; Hsieh et al., 2020; Snijders, 2001), thereby strengthening causal inference in mechanism-based inquiries. For example, recent methodological advances that combine instrumental variable approaches with mediation analysis offer a particularly fruitful direction for studies aiming to rigorously unpack the mechanisms of peer influence (Dippel et al., 2022; Frölich and Huber, 2017; Rudolph et al., 2024; Nicoletti et al., 2023; Carter et al., 2021).

Furthermore, the study's reliance on peer networks defined solely at Wave I of the Add Health data may obscure important temporal patterns. Given the dynamic nature of adolescent friendships, changes such as the creation and dissolution of social ties occurring between the initial network measurement and the subsequent outcome assessment are not accounted for. Consequently, these network dynamics could impact the estimation of peer effects over this period. Future research could advance understanding by moving beyond a static view of network structure to employ more dynamic, longitudinal network analytical approaches.

Finally, while the findings confirm the mediating role of educational motivation in the peer effects on academic achievement, it should be acknowledged that this is not the dominant mechanism. The relatively modest indirect effect sizes observed could, on one hand, stem from the operationalization of educational aspirations and expectations. These

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measures may not fully capture all dimensions of these motivational constructs (e.g., the type or prestige of college aspired to, beyond simply the desire to attend). On the other hand, it is plausible that explicitly stated expectations genuinely account for only such a proportion of the total peer effect, which highlights an avenue for future research to examine other mechanisms. Researchers might draw on recent insights from cultural and cognitive sociology (Cerulo et al., 2021; DiMaggio, 1997; Smith et al., 2020), investigating, for example, whether cultural schema (Boutyline and Soter, 2021) or "non-declarative personal culture" (Lizardo, 2017) offers greater explanatory power. Specifically, future studies could combine social network analysis with the Implicit Association Test (IAT) to measure non-declarative cultural capital (van der Waal et al., 2024) and assess its mediating role in the transmission of educational outcomes among peers. Therefore, the framework presented in this study can serve as a starting point for accumulating further research toward a deeper understanding of how peer influence operates.

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Appendix A — Additional Tables for Main Results

Table A.1. Selected Coefficients in Mediator and Treatment-Induced Confounder Models

DEPENDENT VARIABLE	(a1)	(a2)
	PARTIAL EFFECT OF PEERS' MEAN GPA (A)	
Peers' Mean Educational Motivation (Exposure-Induced Confounders, Z):		
Peers' educational aspiration	.076*** (.015)	.097*** (.017)
Peers' educational expectation	.101*** (.017)	.125*** (.018)
Ego's Educational Motivation (Mediators, M):		
Educational aspiration	.059** (.020)	.073** (.022)
Educational expectation	.055** (.018)	.068*** (.019)
Individual and family covariates	✓	✓
Peer covariates	✓	✓
Grade fixed effects	✓	✓
School fixed effects		✓

Note: $N = 8{,}788$. Estimates are combined across multiple imputation data sets, with the sampling weight applied. SEs are computed using the cluster bootstrap.
†$p < .1$; *$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed tests).

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Table A.2. Selected Coefficients in Outcome Models

	(a3)	(a4)	(a5)	(a6)
	Educational Aspiration		Educational Expectation	
Peers' Mean GPA:				
A	.169***	.105***	.168***	.104***
	(.014)	(.015)	(.014)	(.015)
Ego's Educational Motivation:				
M	.068***	.064***	.101***	.101***
	(.013)	(.013)	(.014)	(.014)
$M \times A$	.030**	.026*	.030*	.029*
	(.012)	(.012)	(.012)	(.012)
Peers' Educational Motivation (Residualized):				
$Z^{\perp}$	-.016	-.007	-.009	-.013
	(.020)	(.020)	(.015)	(.014)
Individual and family covariates	✓	✓	✓	✓
Peer covariates	✓	✓	✓	✓
Grade fixed effects	✓	✓	✓	✓
School fixed effects		✓		✓

Note: $N = 8{,}788$. Estimates are combined across multiple imputation data sets, with the sampling weight applied. SEs are computed using the cluster bootstrap.
†$p < .1$; *$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed tests).

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Appendix B — Difficulties and Solutions for Identifying Causal Peer Effects

Researchers seeking to infer causal impacts based on observed similarities among social ties or within social network clusters will encounter several identification challenges, including confounding due to peer selection, confounding from omitted variables, and the reflection problem (for a review, see An et al., 2022; VanderWeele and An, 2013). First, since the formation of peer groups is not random, observed associations of characteristics among friends may not result from the alters' characteristics causally influencing the ego's characteristics (peer effect), but rather from the ego selecting that alter due to their similarity in the beginning. This peer selection phenomenon, also known as homophily or sorting, describes the tendency of individuals to form relationships with others who are similar to themselves, as evidenced by several previous studies (e.g., Flashman, 2012; Hong, 2025). Consequently, homophily bias complicates the isolation of true peer influence (Shalizi and Thomas, 2011).

A second identification difficulty stems from omitted variable bias introduced by common shocks or shared environments affecting socially connected individuals. This

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bias occurs when the relationship between an ego's and an alter's outcomes is mistakenly interpreted as causal, while it is actually a spurious correlation driven by observed or unobserved factors common to both, such as shared institutional contexts (e.g., the same school) or mutual social circles. For instance, observing high academic achievement in two friends might suggest peer influence. Yet, if both individuals share the same high-quality teachers or benefit from the same supportive school environment, these shared external factors, if unaccounted for in the analysis, could be the true causes of their similar outcomes.

The third challenge is the reflection problem, also known as simultaneity bias. In analyses using group data with unknown internal social interaction structures, distinguishing endogenous from exogenous effects is impossible due to the linear dependency between group mean outcomes and group mean characteristics (Manski, 1993). Even with network data where the individual-specific interaction structure is known, it remains difficult to determine the direction of causality when the interpersonal process is reciprocal and peer effects are defined as "contemporary"—a constraint often imposed by cross-sectional data designs.[1]

Fortunately, the Add Health dataset employed in this study possesses several features that help mitigate the reflection problem. Its longitudinal nature permits the definition

[1] *Group data* refers to settings where information on specific interaction ties within defined groups is absent; individuals are typically assumed to interact homogeneously within the group. Consequently, peer influences are conceptualized based on the aggregate "composition" of the group an individual belongs to (e.g., region, neighborhood, school, or grade cohort). Applying standard linear-in-means models to such data inevitably encounters the reflection problem, as the endogenous effect (group mean outcome) is collinear with exogenous effects (group mean characteristics). On the other hand, if researchers obtain *network data* containing information on specific relationships among pairs of individuals within the group (like how each individual nominates specific friends in Add Health), the individual-specific peer network can be represented by a spatial weights matrix in a spatial autoregressive (SAR) model. Then, both endogenous and contextual effects are identifiable in the SAR model, thus avoiding the reflection problem, as long as there is some variation in social interaction patterns across individuals (Lin, 2010). For a comprehensive discussion of identification challenges and strategies corresponding to different types of social interaction data, see Hsieh et al. (2019).

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of peer effects based on *lagged* friends' outcomes. Thus, using peers' past behavior to predict an individual's own behavior ensures the proper temporal ordering and avoids reverse causality. Moreover, Add Health provides individual-level friendship nomination data, enabling the estimation of influence from self-selected peers rather than relying on aggregate peer group measures (e.g., school-level demographic composition). However, while these study designs help address the reflection problem, homophily bias and confounding due to shared environments (collectively referred to as *network confounding*) remain major concerns and are the focus of the following discussion.

Using network data from the longitudinal survey, the empirical model for peer influences can be specified as:

$$y_{i,r,t+1} = \gamma \frac{1}{g_{i,r,t}} \sum_{j=1}^{n_r} g_{ij,r,t} y_{j,r,t} + x'_{i,r,t}\beta_0 + \frac{1}{g_{i,r,t}} \sum_{j=1}^{n_r} g_{ij,r,t} x'_{j,r,t}\beta_1 + \eta_{r,t} + \epsilon_{i,r,t} \tag{B.1}$$

, where $y_{i,r,t+1}$ is the academic achievement for individual i in network r measured at time $t+1$, and $y_{j,r,t}$ is the academic achievement for an alter j ($i \neq j$) in the same network r at the previous time point t. Similarly, x' is a vector of observed characteristics (other than academic achievement) either for ego i or alter j. Moreover, the adjacency matrix of friendship networks is denoted by g_{ij}, as $g_{ij} = 1$ if i and j are friends; otherwise, it equals 0. Also, $g_{i,r,t} = \sum_{j=1}^{n_r} g_{ij,r,t}$ represents the total number of friends individual i has in network r. Finally, $\eta_{r,t}$ denotes the network fixed effect that accounts for both observable and unobserved factors constant within a given network g.

In this model, the parameter of interest is the coefficient γ, which captures the linear endogenous peer effect, representing the influence of friends' past achievements on the focal respondent's current achievement. Note that this coefficient is multiplied by the

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term representing the average academic achievement of the alters with whom the ego is befriended (i.e., $g_{ij} = 1$), which serve as the treatment variable in my research question. On the other hand, β_0 and β_1 represent the effects of an individual's own characteristics on their outcome and the influence of peers' characteristics on the individual's outcome (exogenous peer effects), respectively. Although such exogenous peer effects can be of significant interest in their own right (e.g., Fletcher et al., 2020), I treat them primarily as control variables and nuisance parameters here. That is, rather than being given causal interpretations (Keele et al., 2020), the ego characteristics term and the peer characteristics term are included in the model to better isolate the endogenous peer effect and address network confounding.

As described earlier, the endogenous peer effect estimate, γ, is susceptible to bias from network confounding arising from two sources: (i) friendship links (g_{ij}) are non-random and endogenous due to homophily bias, and (ii) shared environmental factors that simultaneously affect the outcomes of both an individual and their friends (y_i and y_j) can confound peer effect estimates. To resolve these confounding issues in network influence models, several broad approaches have been developed (for a review, see An et al., 2022; Bramoullé et al., 2020). The first approach involves experimental designs, such as the random assignment of roommates (Guo et al., 2015). These experiments aim to identify causal peer effects by randomly manipulating peer characteristics or the structure of social interactions, thereby enabling isolation of social influence from peer selection. Nevertheless, such randomized experiments are often impractical, unethical in many situations, or unfeasible when only observational data are available.

Second, the instrumental variable (IV) approach has also been employed to identify peer effects. Proposed instrumental variables include friends' family characteristics

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(An, 2015; Fletcher, 2012), indirect peers' characteristics (Bramoullé et al., 2009), and friends' genes influencing the focal outcome (O'Malley et al., 2014). For instance, characteristics of peers of peers have been argued as valid IVs for endogenous peer effects, as these characteristics are presumed to influence the ego's behavior only through the alter's outcome (Bramoullé et al., 2009). While the IV approach offers a way to exploit exogenous variation to address network confounding, it relies on other stringent identification assumptions, such as relevance and the exclusion restriction.

The third approach involves applying statistical correction methods to mitigate network confounding bias. One strategy is to model the peer selection process, accounting for how observed and/or unobserved factors drive friendship formation using techniques like Exponential Random Graph Models (ERGMs) or latent space models. The estimated selection process is then used to correct for bias in the peer effect model (Hsieh and Lee, 2016; Hsieh et al., 2020). Another related method is Stochastic Actor-Oriented (SAO) Models, which explicitly model the co-evolution of network and behavior dynamics, thereby enabling researchers to disentangle social influence processes from tie formation (Snijders, 2001). However, these sophisticated modeling approaches are typically computationally demanding and rely on strong assumptions regarding micro-behaviors and specific parametric forms, which may limit their applicability.

While the aforementioned methods, along with continually developing approaches such as the use of double negative controls (Egami and Tchetgen, 2024), offer various means to effectively address network confounding issues, each operates under distinct assumptions and presents unique implementation challenges. More importantly, they are not readily extended for the current purpose: to decompose the overall peer effect on academic achievement, γ, into an indirect pathway mediated by educational expectations

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and a direct pathway that includes all other mechanisms. As a result, to minimize network confounding, I combine several complementary identification strategies (conditioning on extensive covariates, group-fixed effects, and lagged outcome) that are described in the main text.

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Appendix C — Distributional Peer Effects

Do high-achieving and low-achieving peers have the same, symmetric effect? Traditional approaches often only focus on the central tendency of peer effects, conceptualizing influence as operating primarily through the group's mean characteristics (e.g., average academic achievement). This linear-in-means perspective typically assumes that peer effects are symmetric; that is, high peer achievement benefits students to the same extent that low peer achievement harms them. However, this assumption has been increasingly challenged on both theoretical and empirical grounds (Lavy et al., 2012b; Lee and Lee, 2020; Fujiyama et al., 2021; Bond et al., 2017). To move beyond the average-based estimates and explicitly test whether peer influence is symmetric across the distribution, I compare the impact of high- versus low-achieving peers, assessing differences in effect magnitude and whether both operate by influencing educational motivations to the same degree.

Results examining potentially non-linear, asymmetric peer effects on academic performance are reported in Table C.3. Models 5 and 7 estimate the impact of exposure to low-achieving peers (percentage of friends in the bottom 10% of GPA across the entire sample distribution), while Models 6 and 8 estimate the impact of exposure to high-

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Table C.3. Effects by Peer GPA Percentile Group

	(5)	(6)	(7)	(8)
ESTIMAND	Educational Aspiration		Educational Expectation	
Exposure:	Bottom 10%	Top 10%	Bottom 10%	Top 10%
RATE	-.069*** (.015)	.112*** (.015)	-.067*** (.015)	.111*** (.015)
RNDE	-.068*** (.015)	.111*** (.015)	-.063*** (.015)	.111*** (.015)
CDE	-.074*** (.017)	.118*** (.015)	-.066*** (.018)	.122*** (.016)
$RINT_{ref}$	.006 (.005)	-.007 (.008)	.003 (.008)	-.012 (.012)
RNIE	-.001 (.001)	.000 (.001)	-.004* (.002)	.000 (.002)
RPIE	-.002 (.002)	.000 (.001)	-.004* (.002)	.000 (.002)
$RINT_{med}$	.000 (.000)	.000 (.000)	.000 (.000)	.000 (.000)
Individual covariates	✓	✓	✓	✓
Peer covariates	✓	✓	✓	✓
School fixed effects				

Note: $N = 8{,}788$. Estimates are combined across multiple imputation data sets, with the sampling weight applied. SEs are computed using the cluster bootstrap. Exposure is the percentage of peers by GPA percentile.
†$p < .1$; *$p < .05$; **$p < .01$; ***$p < .001$ (two-tailed tests).

achieving peers (percentage of friends in the top 10% of GPA). These specifications allow us to test whether extreme peers exert differential influences on adolescents' academic achievement.

The total effects (RATE) align with theoretical expectations. Exposure to low-achieving peers significantly reduces students' own overall GPA by approximately 0.069 – 0.067 standard deviations, while high-achieving peers raise motivation by about 0.111 – 0.112 standard deviations. These patterns support both the "bad apple" model, where disruptive

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or under-performing peers harm the entire group, and the "shining light" model, in which high-achievers benefit others (Lazear, 2001; Sacerdote, 2011).

Comparing the effect sizes of the two peer exposures reveals only a slight asymmetry: the positive effects of top-performing peers are marginally stronger (approximately 1.6 times larger in magnitude) than the negative effects of low performers. This modest difference suggests that, while peer ability level matters, its distributional asymmetry may be of limited consequence in the current setting.

More importantly, across all models, there is little evidence that these distributional effects operate through changes in students' educational aspirations or expectations. The indirect effects and interaction effects are consistently small and statistically insignificant for both high- and low-achieving peer groups, with the minor exception of a very small, negative mediation effect for low-achieving peers through lowering one's expectations. These results suggest that when we define peer influence based only on those at the extremes of the GPA distribution, they operate primarily through direct mechanisms, rather than by altering students' educational motivation. For instance, low-achieving peers might create negative externalities through classroom disruption or by requiring disproportionate teacher attention (Lavy et al., 2012a), and high-achieving peers might also influence others through mechanisms not captured by these specific motivational measures.

To conclude, the distributional analysis reveals that both low- and high-achieving peers shape academic performance through direct pathways, with only modest asymmetry in effect size. In this context, considering the central tendency (the average) of peer achievement appears to be a sufficient summary of the peer environment's overall impact. Notably, these distributional peer effects on academic achievement seem to operate

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primarily through pathways other than the measured motivational mediators, as indirect effects via these variables were absent in the decomposition analysis.

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